Active Perception at the Architecture Level

(Extended Abstract)

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1. INTRODUCTION

BDI agents rely on a set of beliefs, while looping in an action-perception cycle. The set of beliefs contains, among other things, the agent's beliefs about the world. These are the end result of a *perception process* which uses sensors and computation power in order to receive, fuse, filter and process information about the environment, to acquire new beliefs, and revise existing ones.

Ketenci et al. [4] and So et al. [9] describe two principled types of perception generating these beliefs. A top-down process, known also as *active perception*, is ideally controlled by the goal-oriented reasoning process, enables the agent to turn its perception—by taking actions—to the most relevant aspects of the environment according to its task. A bottom-up process known also as *passive perception* ideally originates from the sensors, allowing goal-independent, and opportunistic perception.

In physical environments, passive perception is not enough. The agent's resources that are assigned to the perception process are bounded; sensors have limited capabilities (e.g. range, distance and more) and objects may be occluded, out of range, etc.

Unfortunately, current BDI systems and particularly BDI robotic agents use only passive perception. In existing formulations of BDI, the basic assumption is that the agent has all relevant beliefs, but what about the cases where an agent needs to take an action in order to change the state of its beliefs?

In recent years, designers of intelligent agents have been using active perception capabilities in physical environment.

Unfortunately, the majority of the research in the field of active perception deals with specialized algorithms for specific tasks. In particular, there is little or no discussion of active perception capabilities as part of a BDI loop, i.e., at the architecture level. Instead, active perception is folded into the task-specific plans and perceptual models of the agent.

In this article we investigate how active perception is to be integrated in a BDI loop. We present different possibilities for such extended BDI loops and compare them analytically. We draw conclusions as their relative merits and run-time complexity. One algorithm emerges a clear winner over the others.

2. BACKGROUND AND RELATED WORK

Specific instances of active perception—for specific tasks—have often demonstrated the usefulness of this capability [5, 8, 6, 3, 10]. For example, Alomonois et al. [1] prove that vision problems can be solved much more efficiently by an active observer than by a passive one. Ballard [2] shows that the visual computation of systems with active gaze control mechanisms is vastly less expensive than passive systems. However, these algorithms provide ad-hoc solutions for a specific problems. Our approach is to enable an agent the use of active perception capability as part of its architecture.

Weyns et al. [11] present a general model for active perception, composed of three functionalities: *Sensing*, which maps the environment to *representation*; *interpreting*, where the agent turns *representation* to *percepts* (in BDI: *beliefs*); and *filtering*, where the agent can give attention to the most relevant information in the context of its current task. They suggest a reusable framework that allows active change of the agent's perception process parameters to improve perception. Our work is different in two ways. First, while Weyns et al. focus their work on low-level actions, we address also high-level behaviors (e.g. move inside room to get a better look). Second, our work focuses on the integration of active perception in the agent's decision making not just in the perception mechanism itself.

So et al. [9] use *situation awareness* (SA) as a meta mechanism that able to switch between top-down goal-driven and bottom-up data-driven models of information processing. Their model uses projection to the near future in order to deal with top-down goal-driven processes: context and/or precondition clauses determine beliefs that need to be refreshed. Our work is different in several ways. First, So et al. suggested that the active perception process will be triggered whenever it is needed. However, they left the question of integration of active perception in the agent's decision making mechanism open. Furthermore, our mechanisms do not use future projection of the agent's state but plan's clauses only. And last, we extend So et al's. definition for beliefs that are relevant to active perception plans

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by taking under consideration beliefs whose value was never known.

3. ACTIVE PERCEPTION IN A BDI LOOP

3.1 The Basic BDI loop

We focus on enhancing BDI architectures with active perception capabilities. However, there is no single standard algorithm of a BDI architecture.

We therefore turn to the original algorithm presented by Rao et al. [7]. Rao et al's architecture uses three dynamic data structures for the agent's beliefs, desires and intentions together with an input queue of events.

The information about the means of achieving certain desires represented as plans. Each plan has a body which describes the subgoals or simple action needed to be done in order for the plan to be successful. Each plan has preconditions that specifies the conditions that must hold for the plan to be executed. Often pre-conditions are represented as first order logic formulas over the agent's beliefs.

3.2 Architectural Active Perception

Rao et al's architecture makes an implicit assumption that an agent has a full set of beliefs covering any aspect of the world. However, realistically, some belief values may be *unknown* or *outdated* (suspected to be no longer correct). Therefore the assumption that the decision-making process can use the beliefs values during run time fails.

In this article we deal with the problem of weaving active perception plans into a BDI loop. In order to do so it is necessary to modify the basic BDI algorithm so it will be able to consider the execution of a goal driven process which its goal is to update a set of unknown or outdated beliefs.

Specifically, the role of *active perception* process is to *reveal missing beliefs* in order to define whether a plan is feasible (a feasible plan is a plan whose preconditions are true).

We define the *missing beliefs* as unknown or outdated beliefs that are necessary for an agent selecting and executing a considered plan p during run time. When their value is not known, the agent cannot apply the selection and termination mechanisms and also can not guarantee the execution of the selected plan. Therefore *missing beliefs* are the beliefs that require application of active perception process, to determine their value. Here, we focus on beliefs used in testing preconditions.

By applying a series of active perception plans, one can eliminate all missing beliefs associated with a plan. This process is called *revealing.*

3.3 Possible Integrated Active Perception

We developed four algorithms that integrate active perception in the BDI loop. Each algorithm is an incremental improvement over its predecessor. The first algorithm (IAP), executes active perception plans for every *missing belief* of the agent. There are two cases where the use of IAP algorithm is optimal. The first, is when the agent must reveal all the candidate plans, in order to select the best one. The second is when there is no cost for executing active perception processes. In this case, by performing all the active perception process the agent guaranty the selection of optimal plan with no additional cost. however, we show that IAP is likely to execute unnecessary *active perception* plans therefore its cost is high.

The ITAP algorithm allows the agent to myopically select between running an active perception or executing a feasible plan instead, thus limiting the number of active perception plans that are executed. In ITAP, compared to IAP, the agent will execute an active perception process only if it has been selected. Therefore, in cases where active perception processes has costs, the agent can choose and execute a candidate to the optimal plan from the set of feasible plans at any iteration and does not must execute first all the *active perception* plans. However, we show that using ITAP may lead to inefficiencies caused by its myopic selection.

The SAP algorithm resolves these inefficiencies, by taking under consideration the relations between the active perception processes and the plan they reveal. SAP requires the agent to commit to a plan to be revealed, before executing all the active perception plans that reveal it. Once the selection has been done, if it is necessary the agent will execute a series of active perception processes. Finally, if the plan become feasible, the agent can either choose it for execution or select another candidate. The disadvantage of SAP is that it runs the active perception plans in a random order. Although the order of execution is not important for revealing a chosen plan, it is useful to allow the agent to choose the order of execution.

Finally, the DSAP algorithm, allows the agent to choose and commit to revealing a single plan and then allows the agent to choose again the next *active perception* plan within the domain of plans who support the selected one.

3.4 Comparison summary

In the article we present four algorithms that integrate BDI architecture with active perception. The main difference between the algorithms is the use of the deliberation mechanism. From our work it seems that there are major differences. While IAP does not allow any deliberation over the suggested *active perception* and executes all of them, ITAP is losing information and this makes the deliberation mechanism inefficient. SAP overcomes ITAP's difficulties by using the information about connection between the active perception plans. And finally, DSAP improves SAP's performance by allowing the use of heuristic functions for a second selection.

4. CONCLUSION AND FUTURE WORK

A basic building block in BDI is the set of beliefs an agent has over the world. However, in many cases due to the characteristic of the environment, there is no promise that during run time the beliefs' values will be available. active perception processes are the solution for handling missing beliefs during run time. However, in most of the cases they are used as ad-hoc solutions for a specific need, and are therefore assumed to be interleaved with the actions taken by the agent when it executes it domain-dependent plans.

The purpose of this article is to deal with active perception at the architecture level, specifically within the BDI loop. We present four algorithms that integrate active perception into the classic BDI loop. We show that different methods of integration create major differences in the running time of the algorithms. Finally, we suggested the DSAP algorithm that takes under consideration the limited available information in order to minimizes the amount of time the agent has to invest in execution of active perception processes.

REFERENCES

[1] J. Aloimonos, I. Weiss, and A. Bandyopadhyay. Active vision. *International journal of computer vision*, 1(4):333–356, 1988.

[2] D. H. Ballard. Animate vision. *Artificial intelligence*, 48(1):57–86, 1991.

[3] D. Fox, W. Burgard, and S. Thrun. Active markov localization for mobile robots. *Robotics and Autonomous Systems*, 25(3):195–207, 1998.

[4] U. G. Ketenci, J.-M. Auberlet, R. Brémond, and E. Grislin-Le Strugeon. Improved road crossing behavior with active perception approach. In *Proc. Transportation Research Board Annual Meeting*, 2012.

[5] D. Kinny, M. Georgeff, and J. Hendler. Experiments in optimal sensing for situated agents. In *Proceedings of the Second Pacific Rim International Conference on Artificial Intelligence*, pages 1176–1182, 1992.

[6] Q. V. Le, A. Saxena, and A. Y. Ng. Active perception: Interactive manipulation for improving object detection. *Standford University Journal*, 2008.

[7] A. S. Rao and M. P. Georgeff. BDI agents: From theory to practice. In *ICMAS*, volume 95, pages 312–319, 1995.

[8] C. Schlegel, J. Illmann, H. Jaberg, M. Schuster, and R. Wörz. Integrating vision based behaviours with an autonomous robot. In *Computer Vision Systems*, pages 1–20. Springer, 1999.

[9] R. So and L. Sonenberg. The roles of active perception in intelligent agent systems. In *Multi-Agent Systems for Society*, pages 139–152. Springer, 2005.

[10] A. Unterholzner, M. Himmelsbach, and H.-J. Wuensche. Active perception for autonomous vehicles. In *IEEE International Conference on Robotics and Automation (ICRA)*, pages 1620–1627. IEEE, 2012.

[11] D. Weyns, E. Steegmans, and T. Holvoet. Towards active perception in situated multi-agent systems. *Applied Artificial Intelligence*, 18(9-10):867–883, 2004.