Active Memory-based Interaction Strategies for Learning-enablingBehaviors

Marc Hanheide and Gerhard Sagerer
Faculty of Technology, Applied Computer Science, Bielefeld University, 33594 Bielefeld, Germany
{mhanheid,sagerer}@techfak.uni-bielefeld.de

Abstract—Despite increasing efforts in the field of social robotics and interactive systems integrated and fully autonomous robots which are capable of learning from interaction with inexperienced and non-expert users are still a rarity. However, in order to tackle the challenge of learning by interaction robots need to be equipped with a set of basic behaviors and abilities which have to be coupled and combined in a flexible manner. This paper presents how a recently proposed information-driven integration concept termed “active memory” is adopted to realize learning-enabling behaviors for a domestic robot. These behaviors enable it to (i) learn about its environment, (ii) interact with several humans simultaneously, and (iii) couple learning and interaction tightly. The basic interaction strategies on the basis of information exchange through the active memory are presented. A brief discussion of results obtained from live user trials with inexperienced users in a home tour scenario underpin the relevance and appropriateness of the described concepts.

I. INTRODUCTION

Robots that are not only working on their own, but entering people’s every-day lives in order to entertain, assist, or accompany become more and more visible these days. We have witnessed a boost of research in the areas of social and cognitive robotics in the last decade, motivated by the goal to achieve more flexible applications and more intuitive interaction between humans and robots. In order to provide the required flexibility, continuous interactive learning is in particular relevant and an emphasis of cognitive robotics in general.

A. Learning as a Social Task in Robotics

Following the argument of Breazeal [1] and others, we assume that it is one general goal of social robotics research to enable people who are not particular educated in robotics to operate and interact with complex robotic systems. This vision is based on the conviction that social abilities implemented in robotic systems can pave the way towards universal and intuitive interfaces.

A most compelling issue for robotics is however to evolve from pre-programmed behaviors and fixed scenarios towards real-world environments and adaptive abilities. This in particular requires novel paradigms that go beyond defined training and test sets as known from machine learning, but demand for a continuous validation and adaptation of acquired models, embedded in the interaction itself. This embedding of learning has recently been mentioned as “socially guided machine learning” [17]. However, looking onto integrated, larger scale systems, learning in cognitive or intelligent robotics is a process neither being isolated in one particular component nor is it one single general independent ability. In fact, it is rather a feature effecting the whole system, crossing components’ borders, and demanding for a systemic treatment and design. Consequently, we exploit a more general paradigm here, “learning by interacting”, abstracting from particular machine learning techniques and excepting learning as a general and systemic challenge.

In this paper, we present a set of behaviors which to our conviction are mandatory in order to enable learning in an interactive manner (Sec. II). With these behaviors at hand we present how the active memory concept is applied in order to integrate the different ones into a learning-enabled interactive robot (Sec. III). The general concepts which evolved from a constructivist approach of actually building systems, are illustrated using exemplary use cases taking a deeper look into the control flow of the system. Following our conviction that these kinds of interactive robotic systems have to be evaluated in the context of their field of application, some of the results gained from an evaluation study with non-expert users are presented in Sec. IV.

B. The Home Tour Challenge

The general scenario we are interested in for learning is widely known as the “robot home tour”. It follows the vision of a (service) robot being delivered to peoples’ houses without prior knowledge about the particular environment. But it comes equipped with capabilities that allow it to learn...
in an interactive fashion. Afterwards, the robot is expected to be able to provide services in a user- and situation-aware manner. The “home tour” is mainly focused on the interactive acquisition of human-adequate representations and the interaction itself rather than on any specific service. Knowledge to be of interest thereby comprises topological representations of the living space, models about relevant objects and functional spaces, and about different users. The latter aspect is in particular relevant because a robot is considered to be a servant or companion interacting for instance with the various members of a family. The “home tour” scenario recently also gained particular interest by related projects (e.g. in [12]) and by the RoboCup@Home competition\(^1\).

In order to tackle real-world challenges we permanently rent an apartment (see Fig. 1(a)) to move out of the lab into realistic settings and let non-expert users interact with it regularly. The goal of the home tour is to enable non-expert users to teach a robot about their own living environment in a rather intuitive way, emulating human-human interaction to a certain extent. Hence, interaction between the robot and the user shall be driven by social cues and conducted in a most flexible manner. The user is engaged in interaction with the robot by means of verbal dialog, joint spatial exploration, and gestural reference, to mention only some relevant abilities. Resulting real-world challenges ranges from small doorways, uncontrolled visual and acoustic conditions to unpredictable human behaviors and reactions.

II. LEARNING-ENABLING BEHAVIORS

What is interactive learning about? We are convinced that it is to a large extend about (joint) multi-modal attention and interaction management including perception and feedback, interweaved with autonomous capabilities to actively explore the environment. This view is widely backed by many researchers in social robotics [5]. In order to facilitate learning we assume a set of basic behavioral skills as being innate to a robot capable of learning by interaction. In the following, a selection of most relevant learning-enabling behaviors implemented on our robot BIRON shown in Fig. 1(b) is briefly outlined. These behavioral building blocks need to be coordinated, synchronized, and partially concurrently executed. When talking about behaviors here, these are defined as functionalities that link sensors and actuators; not necessarily but often in a rather reactive fashion, though still considering global and local states. A more detailed description of the involved algorithms that realize the behaviors is presented in several publications ([16], [11], [6]) and in a paper [8] describing a predecessor of the system. However, many more behaviors such as emotional mirroring, imitation, curiosity, and joint attention using gestures are facilitators for interactive learning and partially available on BIRON as well. Though, only a closer look on three selected behaviors shall be taken here for the sake of clarity.

\(^1\)www.robocupathome.org

A. Interaction Partner Attention

In order to allow human-oriented interaction the robot must be enabled to focus its attention on the human interaction partner; and in parallel also be aware of other surrounding and potentially interacting humans. By means of an actively controlled video camera to detect faces, a set of two microphones for voice direction perception, and a laser scanner applied to detect pairs of legs (see Fig. 1(b)) it is possible to perceive and continuously track multiple people in real-time in the robot’s vicinity [6]. The behavior controls the camera in order to actively keep track of the different persons and also to perceive their faces. This behavior is one example for a continuously running one, because the robot should try to maintain a mutual link with its interlocutor by tracking her all along.

B. Person Following

Following a person is a key competence of a mobile domestic robot to interactively learn about the environment. Based on the attention and tracking of the interaction partner outlined above the robot applies a reactive obstacle avoidance and short distance path planning [13] in order to follow a person in a socially adequate way. On user’s request the robot starts following her until she ask it to stop. The integrated obstacle avoidance allows the appliance in narrow apartments as well. It shall be noted, that this behavior needs be running in parallel to the interaction partner attention.

C. Autonomous Exploration and Data Acquisition

In order to facilitate comprehensive learning, the robot must actuate its sensors to collect data in an active manner. As an example for this use case, the “human augmented mapping” [2] which exploits geometrical measures obtained using the laser scanner to build up a topological representation shall be mentioned. Whenever it gets to know a new location (e.g. “kitchen”) it captures a 360° scan by autonomously turning around. In our notion, this constitutes an autonomous behavior, requiring for proper coordination and arbitration in order to avoid conflicts with other behaviors, e.g. interaction partner attention which also actuates the robot’s wheels.

III. AN ACTIVE MEMORY FOR A LEARNING ROBOT

A memory is seen as a foundation for any further cognitive processing in general and for learning in particular. Is has become apparent that cognitive systems demand for close coupling between representation and processing [7] to facilitate learning and extensibility. Motivated by this assumption, we propose a system architecture that emphasizes the role of knowledge acquisition and information exchange on a systemic level. It will be demonstrated how the exchange and acquisition of information can be the driving force for the robot’s behavior applying a concept known as the Active Memory (AM) [18].
A. The Active Memory for Information-driven Integration

The concept of an active memory (AM) for building cognitive systems has been proposed already some years ago.

It basically puts forward the concept of event-driven integration on the basis of flexible notification and XML-based representations as a document-oriented data model. In particular it comprises an “active memory server” (AMS) which constitutes the basis for coordination and shared data management. Basically, all information generated and revised by components in the systems is mediated through this active memory, where it can persistently be stored and retrieved from.

Components can register on particular fragments of information by means of XPath subscriptions and get notified whenever this subscribed memory content changes or shows up in the memory. Hence, operations that modify the memory’s content are insert, remove, replace as also illustrated in Fig. 2. These resemble functionalities of databases systems as well as the also available query operation. Components in this concept are termed memory processes that generate, receive, and interpret information and are locally triggered by the exchange of the information atoms, so-called memory elements through respective subscriptions. The AMS itself can be seen as a global state space, providing coordinated read-write access to all memory processes, resembling some concepts of blackboards [4]. For more details regarding the principles of active memories refer to [18].

B. Dialog Management

Picking up the idea to incorporate user interaction in the learning task leads to the question of an appropriate interface to the human. A dedicated dialog component which manages the exchange of information with the user is an integral element of the proposed concept. In a simplified view, the dialog serves as an adapter to the active memory that submits information provided by the user as memory elements or activities modifying the memory content are displayed dark, others in lighter. XML fragments are drawn alongside the activities.

Hence, very generic processes such as the “forgetting”-process described in Sec. III-E can easily be developed.

1) Location Learning with Autonomous Exploration: To illustrate the idea, it will be shown how a state encoded in the meta-data of memory elements can facilitate the coordination of learning-enabling behaviors. We will discuss how the interactive learning of new rooms is realized and coordinated by a rather simple but generic state machine in memory elements, leading to a quite powerful interaction strategy. It illustrates how this interaction strategy allows to sequence and arbitrate behaviors on the robot. The use case is as follows: The robot is following the user (following behavior) during the home tour and the user teaches a new room (in our example: the kitchen).

The whole process is sketched in the activation diagram of Fig. 3. The learning itself is embedded in a more complex interaction between the system and the user, and in consequence, between different behaviors of the system. After parsing and interpreting the user’s utterance the “Dialog” inserts a new memory element LOCATION into the active memory, containing a meta data tag state with content initiated. In the notion of the AM concept, the Dialog serves as an adapter to the human, providing the information given by the user (“This is the kitchen”) to the robot’s short-term memory. In Fig. 3 the control flow now branches because the system can work with two different approaches to actually learn locations. First, we will describe the path labeled “[method=exploration]” and leave the other for later discussion in Sec. III-C.2.

An arbitration component [15] which globally controls the device and hardware access of the robot is subscribed to get triggered whenever a memory element (XML document) containing the root tag LOCATION is inserted. It now allows the “Location Learning” to take control of the robot’s
driving motors. In order to communicate the successful arbitration no explicit notification of any other component is done, but the state of the memory element is changed to accepted. The ME itself is still the same but it has been updated. This update now triggers the “Location Learning” which starts an autonomous exploration by turning around in order to gather a 360° laser scan (refer to Sec. II-C).

From the perspective of (machine) learning this autonomous behavior is fine as it fulfills the purpose of data acquisition for learning. However, from user studies we observed that non-expert users are rather surprised whenever the robot starts to autonomously turn around. Here one can spot one major difference between machine learning and social learning: the relevance of feedback. By simply subscribing the “Dialog” to the same update it is able to provide feedback, informing the user about the ongoing behavior.

As soon as the autonomous exploration is finished the “Location Learning” itself updates the state again to inform as well the dialog as the arbitration about the completion of the behavior. In consequence, the robot memorizes the map of the room, and the “Dialog” provides according feedback.

2) Appearance-based Location Learning: In order to illustrated the flexibility of the approach, the second branch (“method=exploration”) of the control flow in Fig. 3 shall be outlined. It is related to an alternative approach of learning the appearance of a room based on an omni-directional camera [14]. The major difference from an interaction perspective is that it does not require the robot to turn, but instead just captures an image from the camera. Learning here is very immediate within half a second. Furthermore, as the robot does not have to turn, no arbitration action is required. What has to be modified in order to get this approach running without any explicit feedback? Using the active memory concept only the subscription of the Arbitration on the LOCATION MEs is removed. There is no need to adjust the “Dialog”. Note, that the implementation of the learning of locations actually comprises some more complex interaction schemes related to mixed-initiative, correction, and ambiguity resolution [16], but all following similar processing schemes. The state interaction strategy turned out to be a very powerful and flexible concept to implement hand-shake-like protocols in the active memory.

D. From Multi-modal Perception to Interaction Partners

In order to illustrate the concept of the active memory further, a third use case is presented: We will discuss the control flow that enables the system to focus on its interaction partner; again by coordination through the active memory. The central behavior realized here has already been briefly outlined in Sec. II-A “Interaction Partner Attention”. It is modeled as a two stage process, namely “anchoring” and “interaction partner selection”, with each its own particular memory-based interaction strategies.

1) Anchoring: Anchoring here is the term for the rather generic conceptual strategy in the active memory of mapping percepts to episodic entities. The goal of this mapping is to achieve and maintain a one to one correspondence between PERSON anchor memory elements (PAME) and real persons of interest (POI) in the robot’s vicinity. Any multi-modal percept is treated as an instantaneous observation, being only valid for the very specific moment in time. The detection of a pair of legs or a face are such kind of percepts which conceptually are fed to the AM also as memory elements that however never get updated. Following the basic concept of multi-modal anchoring [6], a memory process is integrated which is subscribed to the insertion of any relevant percepts and maps them to best matching entities (PAME), as illustrated in Fig. 4.

Conceptually, this process structures the memory into different layers. The short-term memory is characterized the short life time of the memory elements it repositis. Percepts are fed to this layer. The generic anchoring process that takes these perceptual memory elements and fuses them into the scene memory, which hence contains the current partial view of the corresponding real-world scene. Therefore it matches incoming percepts to existing entities in the scene memory and either updates the best matching PAME or creates a new one (cf. Fig. 4) depending on the match quality [10]. The corresponding timestamps are set accordingly. Furthermore, the anchoring can determine the reliability of the PAME on the basis of the quality of the match and updates this information, too. It also assigns attributes such as “talking” and “facing” to each person derived from the current perception. Anchoring in the AM is however not restricted to anchoring of persons from laser, visual, and audio cues, but constitutes a generic process which also has been exploited in other (non-robotic) domains such as visual object and person tracking [10].

2) Interaction Partner Selection: The process of anchoring is also illustrated in the upper part of Fig. 5 as part of the activity diagram. It continuously maintains a set of persons of interest (POI). However, for interaction, the robot usually selects one of these potentially numerous persons of interest as an interaction partner. This selection is the basis for any personalized service and interlocutor-based interaction.

It shall be noted that though the robot is generally capable of mixed initiative the following description will be based on the user initiative case. As soon as the user addresses the robot by e.g. its name, the respective talking person of interest becomes the interaction partner (IP). In order to announce the IP to the system the “Dialog” selects the currently speaking POI as the new interaction partner by inserting an IP memory element (see activity “memorize IP” in Fig. 5). The insertion of an IP memory element
subsequently triggers reconfiguration of different behaviors. The following behavior (Sec. II-B) by this means has the information about whom to actually follow and the interaction partner attention (Sec. II-A) now actively aligns the robot’s sensors to track the selected interaction partner, for instance.

E. The Semantics of Forgetting

Up to know, information has only been submitted or revised in the active memory. We have not yet discussed how an overflow of the memory can be avoided and what happens to outdated information.

1) Removal of Outdated Information: Except for long-term information, configurations, and learned models, most information in the memory shall be removed as soon as it is no longer valid. Instead of designing and implementing “forgetting” again and again for every component the active memory concept proposes a dedicated process of forgetting, again operating on the meta-data of memory elements [18]. For state-less memory elements that need continuous updates to still be valid (e.g. the PAMEs or the IP memory element introduced earlier), forgetting can simply be designed on the basis of time-stamp meta-data. This scheme removes PAMEs from the memory as soon as they are no longer valid, which is defined by an update time-stamp being to long ago. The same can hold for the interaction partner. Any behavior in the system which is interested in a particular person can subscribe on updates of the respective memory element and its removal. Note, that the concept of forgetting on the basis of meta-data also scales to more complex models as for instance described in [9]. According to the definition of percepts being never updated after insertion, an overflow of the memory if also already avoided by applying this simple forgetting scheme.

2) Deadlock Avoidance and Exception Treatment: Applying the forgetting in conjunction with the outlined state-modeling in memory elements also allows for interactive exception treatment. A forgetting process can be designed to also always remove memory elements depending on their state. Let us recall the use case of the location learning (Sec. III-C.1). What happens if the activity “autonomous exploration” cannot be successfully completed, e.g., due to an obstacle blocking the robot? The answer is simple: The memory element will not be updated with state “completed” and in consequence, the whole activity will not finish. However, adding a forgetting process that removes the memory element on the basis of the timestamp avoids the deadlock as long as the involved components are also subscribed to this removal event. Any removal in a state different than “completed” indicates an exception and allows components, in this case the dialog, to act accordingly. In our current implementation, the dialog informs the user about the unsuccessful completion using verbal feedback. Such kind of error treatment is considered in particular important for interactive learning behaviors as only they allow to still establish a common ground between the interlocutors, as will be underlined by some results presented in the upcoming section.

IV. HUMANS’ INTERACTION WITH THE SYSTEM

Learning by interacting as defined in this paper is a joint effort of the human and the robot. The design and coordination of the interactive learning behavior serves simply one goal: To enable a human user to operate the robot in an intuitive and consistent way in order to complete the task, which in this case was to successfully complete the home tour. Therefore, she must be enabled to exploit the implemented learning-enabling behaviors of the robot and to understand its feedback with respect to the learning task at hand. Hence, the systemic evaluation must include the human user engaged in real tasks in order to (i) to assess the current implementation and (ii) to gain insights for an iterative improvement of the behaviors and their coordination.

In order to get the iterative implementation-evaluation cycle going, two consecutive user studies have been carried out up to now in the robot apartment using a prototype [3]. In total, 24 subjects (12 female, 12 male, average age 37.3) interacted with the robot. Their task was to take the robot around in the apartment (requesting the follow behavior), teach two rooms (using the location learning with autonomous exploration), and to also show two objects. The latter learning-enabling behavior has however not been in the focus of this paper. Before they conducted the task they received an introduction to the robot’s basic abilities. An in-depth analysis of the acquired data with regard to

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2See XML fragment shown in Fig. 4; the corresponding XPath for forgetting all information not being updated for about 2 seconds is simple: e.g. /*/TIMESTAMPS/UPDATED[@value<now()-2000], assuming a function now() which evaluates to the current time in milli-seconds.
technical evaluation, behavior-specific performance, or dedicated interaction models would also definitely go beyond the scope of this paper. Taking a closer look into the human-robot interaction reveals that error treatment and exception handling is most crucial in interactively teaching a robot. To give an example: Only about 33% of all tries to teach a room to the robot did complete successfully in the first attempt. Initiating a follow behavior is also not trivial for naive users. Only about 42% are successful in a first attempt. Problems are partially again either related to speech recognition or to difficulties of the system to perceive the interaction partner. But some of these problem are caused by the user’s not behaving according to the implemented models of interaction because they were just not aware of those. However, it is impossible to foresee any kind of user behavior which again emphasizes the relevance of flexible interaction and feedback design. Despite these individual problems, 22 of all 24 subjects actually completed the task successfully in the given time constraint of 15 minutes, showing that the appropriate feedback in learning is necessary and working. Learning by interaction is apparently a closed-loop task here which enables non-experience user to achieve a teaching goal by exploiting the interaction with the robot.

V. CONCLUSION

This paper presented how the concept of information-driven integration based on the active memory can be applied to realize and control interactive learning behaviors. The basic idea is to coordinate the robot’s behaviors by modification and acquisition of information. This in particular allows flexible learning-enabling behaviors supporting mixed-initiative interaction and also flexible substitution of information sources and components, respectively. Learning by interacting and social learning require basic behaviors that enable to learn and consider the whole process of learning as a joint effort. The information-driven concept of the active memory resembles familiar concepts of cognition and hence provides a very vivid metaphor to design systems on the one hand. On the other its sound technical implementation facilitates a straightforward realization of integrated learning-enabling systems. Some relevant memory-based interaction strategies in the AM emerging from a constructivist approach of system design have been identified and discussed. However, an in-depth analysis of the suitability of AM concepts as a novel architectural style for building interactive robotic systems and comparisons against other established architectures is on-going research. Further iterations of implementation and evaluation, not only regarding the home tour scenario, in order to improve feedback, the particular behaviors, and the perceptual capabilities will certainly comprise enough challenges for next future. These need to be tackled in strong relation to ongoing evaluation with users in real environments.

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