A Concept of a Reliable Three-Layer Behaviour Control System for Cooperative Autonomous Robots

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Abstract. Especially in robotic applications with hardly accessible and unknown environments like deep-sea or space missions, two requirements are given: First, the robotic systems need to work reliably and, second, an autonomous operation would increase the efficiency a lot. While the demand for a reliable system behaviour could be satisfied through predefined and tested plans and models, the unknown environment impedes both. Presented is a concept of a reliable behaviour control system that is meant to be used in the context of a lunar or planetary space mission with a loosely-coupled group of autonomous robots. To realize a reliable system behaviour even in unknown environments, the proposed design follows a biologically inspired approach including adaptable prediction and self-evaluation components.

1 Introduction

In the application fields of deep-sea and space robotics, the environment of the robots is usually not known at design time. However, in both cases the reliability of the robotic systems is an important requirement as human intervention (e.g., in case of malfunction of the system) is either impossible or would need a great effort. To use an autonomous system in such a reliability-demanding scenario, the system needs to be tested and verified at design time. Since the environment is unknown at this time such a prior verification is impossible, and therefore a remote control setup is chosen for most of the space robotic scenarios. Due to problems with data transmission in space and deep-sea missions (e.g., package loss or blackout phases), the system's efficiency is reduced a lot. In both application fields working in groups of robots and a parallel usage of an autonomous control together with a remote one could increase the reliability. On the one hand the reliability is given through the redundant sensor data processing by the autonomous robot group and the human operator in parallel. On the other hand fast emergency reactions could trigger even before the triggering sensor data is visible to the human operator. Moreover, in cases of communication breaks, the autonomous control could take over the system control.

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Based on biological and psychological findings and models, the proposed architecture is expected to be adaptive to the environment (e.g., being able to develop new behaviours) and robust in facing new situations (e.g., react on new circumstances). One drawback of many biologically inspired models (e.g., models that are implemented within a single neural net) is their cumbersome extensibility, as new functionality has to be trained and cannot easily be exchanged. Therefore, we present a modular biologically inspired architecture whose initial settings can be given in advance and whose module functionality is much more comprehensible. Additionally, it still benefits from the adaptability and flexibility of biologically inspired systems.

2 Related Work

Several robotic behaviour control architectures have been proposed, including the traditional subsumption architecture [1] and extensions of three-layered models for multi-robot cooperation [2]. However, as behaviour control in animals and humans can be both very robust and efficient, another way to go for a reliable robot control system is to build on findings in biology or psychology. In both disciplines several specific effects have been studied but just a few covered an overall behaviour control. One example for an overall study (specifically behaviour switching) is the architecture proposed by Norman and Shallice [3]. It covers switching between attended and unattended task execution. Another example is the generation of expectations of action consequences based on internal models. These predictions can be compared with the actually sensed percepts during or post action execution (e.g., in biology [4], computational studies [5], [6] (review), and in robotic experiments [7]). Also a non-biologically inspired model-free execution monitoring approach has been proposed [8], which does not require a prediction model before task execution, but learns the normal and faulty execution of behaviours through a supervised learning phase.

Exemplary robotic implementations based on the psychologically inspired behaviour control architectures by Norman and Shallice were proposed by Gurney et al. [9] and Garforth et al. [10]. Gurney et al. implemented the Norman and Shallice model with the application to autonomous vehicle control. The authors tested their system in simulations. Garforth et al. chose the architecture proposed by Norman and Shallice, too. They tested their implementation in simple two-wheeled-robot simulations. In addition, they tried to match the single function blocks of the architecture with specific regions of the human brain.

Given that the Norman and Shallice implementation proposed by Garforth et al. is the most extensive one, we extend their architecture to fit our needs of robustness, modularity and flexibility. For robustness reasons, we introduce a monitoring of action execution in the lowest layer that is based on prediction models that can be learned in advance or at runtime. An advantage of learning prediction models over model-free monitoring approaches is the ability to use the inverse models of the prediction for planning the action execution. As Garforth et al. base their architecture on neural networks, it is difficult to extend the behaviours and their connections to sensor percepts by hand, which impedes the manual design. To emphasise the modularity and flexibility of our architecture, we introduce the concept of triggers that was proposed by Norman and Shallice before, to manually connect sensor perception and behaviours by hand. We will additionally introduce a planning interface on the second layer as well as a cognitive layer on top of it.

3 Three-Layer Behaviour Control System

In figure 1 a simplified overview of the proposed behaviour control system structure can be seen. The lowest layer (*Reactive Layer*) realizes solely reactive behaviours that are activated by specific perceptions. It contains a set of *Actions* that are selected by the *Pre-Selection* through triggers. All of these triggers are activated by a trigger condition in the raw and preprocessed sensor values that can further be processed in the *Episodic Memory.* Actions can be triggered in parallel and each trigger can select several actions. A weight is associated to each selected action that corresponds to the match of this action given the current perception. While executing an action, a so-called *Exafference Computation* compares the sensor states with a prediction based on an adaptable internal sensorimotor loop model (cf. [6]).

The middle layer (*Deliberative Layer*) contains a *Planner*, a *Semantic Memory* for storing general knowledge (e.g., rules applicable at plan generation) and a *Working Memory* for previously generated plans. While executing a plan, a *Monitor* compares the current behaviour to be executed according to the plan with the actions to be executed by the lowest layer. If there is a discrepancy, the *Deliberative Layer* modulates the action selection in the *Reactive Layer* by the *Behaviour Generation and Modulation* to bias the selection of an intended action (i.e., actions matching to the current plan). The selection of *Actions* takes place in both layers in parallel and is then merged into a common list of candidates. Through this non-exclusive action selection, it is still possible that a reactive action is selected instead of an intended action due to a higher weight of this reactive action. This guides the robot system through potential harmful situations (e.g., damaging the hardware or being stuck in fine soil). This, together with the exafference monitoring, is supposed to lead to a reliable system.

When the execution of a plan is interrupted, the *Creative Cognition* can reason about the cause by analysing recent sensor states. While reasoning, new required knowledge for the *Semantic Memory* might be generated that supports the *Planner* and the *Behaviour Generation and Modulation* to generate new plans and behaviours to solve a given situation. This reasoning can also cause the robot to explore the environment in order to fill the knowledge gap for resolving logical contradictions. When a plan is executed several times, a learning in the lowest layer can be triggered (see [10]). Consequently, the lowest layer "learns" an intended plan or a part of it together with the expected sensor consequences as a future triggerable reactive behaviour. The more often this plan is executed in that perceived state, the stronger the connection between sensor perception

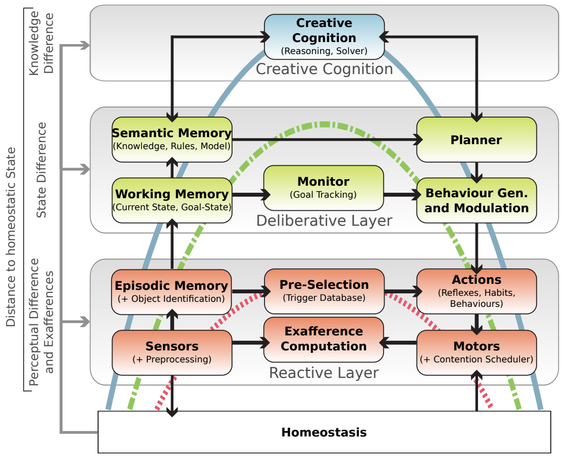

Fig. 1. Overview of the proposed behaviour control architecture.

and action is evolving. This learning over time leads to strong direct connections in the *Reactive Layer*, which are independent from the *Deliberative Layer*.

For an application of the behaviour control system in a group of autonomous robots, a loosely-coupled cooperation without or with reduced explicit communication can be realized. For example, if a robot is recognized by another robot (via the *Object Identification*) a learned reactive behaviour or a plan execution can be triggered (e.g., "go to recognized robot", "unload the recognized robot"). In this group of autonomous robot systems, knowledge in the *Semantic Memory* can be exchanged. The *Semantic Memory* includes, amongst others, the world model and is independent from the sensor modality and the design of the robot. For this reason a robot can obtain needed knowledge from another heterogeneous robot by exchanging and merging world models.

The functions of the components as well as the whole-model behaviour need to be examined separately for two different initial conditions: The *Blank State* and the *Learned State*. In the *Blank State*, all memories, parameters, and learnable connections are empty or randomly initialised. Additionally, as few reflexes, basic behaviours, and internal models as possible and biological plausible are predefined. Starting from this state, the system is supposed to gather all other needed behaviours and models on its own. Since learning on a real system will take a lot of time, a second state, the so-called *Learned State*, will be used for most of the tests and demonstrations. In the *Learned State* the system is supposed to have learned already several behaviours, plans, and models. For sending a robot system into a real mission, the robot can be trained from the *Blank State* into the *Learned State* within a simulator. Equipped with this *Learned State* it continues to extend its knowledge and behaviours in the actual environment.

4 Conclusions and Outlook

Proposed is a biologically inspired reliable control architecture that realises pure reactive and simultaneously deliberative action selection. In addition to the advantages of such biologically inspired architectures (reliability, robustness, flexibility) it also supports the manual design. It is especially designed for missions with groups of loosely coupled robots, where reliable cooperation is a high demand. The self-evaluation through prediction on the lower layer can be used to ensure that the system prevents dangerous states. At the same time the upper layers cover goal tracking and knowledge management also in cooperation with other even heterogeneous robot systems within a mission team.

A prototypical implementation is ongoing and first simulation results of a behaviour switching and the biasing through the deliberative layer were evaluated. The next step is to carry out these experiments on a real robotic platform in a lunar crater model. The scenarios will be designed so that the robot has to adapt to the situation by changing weights of the actions to fulfil its mission. The whole architecture will be evaluated according to these scenarios and comparisons to recently proposed architectures will be made.

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