Cognitive Hybrid Control of an Autonomous Agent

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Abstract

Within the framework of embodied cognition, an artificial agent is let to interact with its environment in order to learn the prediction of multi-modal sensory situations. The agent, a simulated robot, moves in a 2D environment and makes use of a forward model as a basic cognitive tool. The trained system learns to successfully predict a multi-modal sensory representation of obstacles, formed by visual and tactile stimuli. Using a real robot, the trained forward model is coupled with a Bayesian controller. The forward model is fed a covert motor command. When the covert motor command produces a collision-free sensory prediction the motor command is executed. When this is not the case, the Bayesian controller produces a motor command providing a collision free sensory situation by means of probabilistic reasoning. Experiments show that the coupling allows the robot to safely navigate among obstacles in its environment.

1 Introduction

The research presented here focuses on the study of cognitive models and the exploration of their capabilities by implementing them on artificial agents. In this paper, we investigate the coupling of two different cognitive modules. One uses a priori knowledge while the other evolves through interaction with its environment. An important issue in this work is the formation of multi-modal sensory representations, emerging as part of one of the modules. The cornerstone of this research is the importance of prediction and action as part of the perceptual process of a cognitive system.

The research is framed in the field of embodied cognition, which represents a new view of artificial intelligence [13], [14]. Embodied cognition recognizes that agents must have a body and actively interact with their environment in order to learn and understand their surroundings [16].

1.1 Classical Views on Perception and Action

A widely accepted view of cognition explained behaviour as a product of a direct, unidirectional line of information processing. Sensory inputs create a sensory representation and according to this a motor action is performed, actions are regarded as reactions, responses to stimuli. Most of the observed behaviour is considered a consequence of an innate stimulus-response mechanism that is available to the individual [15]. The perception processes is seen as a succession of modules that receive, modify and then pass the information available from the environment.

In the cognitive sciences, artificial life and robotics this framework provided researchers with the opportunity to consider and work on isolated modules with specialized skills [12], [1].

These approaches to cognition present several problems. First of all, at least some behaviours are best developed and learnt when an agent dynamically interacts with the environment [2]. Second the complexity of programming behaviour-specific modules increases dramatically as the number of behaviours is incremented.

The most well-known problem is that of the homunculus. Once a sensory representation is formed there is the need for someone or something to interpret that representation and then perform the required action. This problem presents itself again when the homunculus requires the interpretation of its own sensory representation.

Furthermore, agents developed along this approach fall easily into the well-known grounding problem. This problem is basically the lack of meaning for the agents of learned symbols and of behaviours in a certain environment. These agents did not evolve or learned through direct interaction with their own world [16].

1.2 Anticipation and Action Selection

A novel approach to perception considers sensory input and action (motor output) as part of the same cognitive pro-
In the field of cognitive psychology these ideas have recently received much attention. A general framework is based on the ideomotor views of action control. These views stress the role that internal mental states such as goals or intended actions play in the realization of actions, disregarding to different extents the external sensory conditions.

Perception and action have been linked functionally. It is this link and its coordination that provides the basis for adaptive behaviour [7], [4]. Within this framework, sensory representations are also considered as consequences of actions. Any action realized by an agent on the environment has effects (action effects) and are the main reasons for behaviour. Representations that code for the environmental and bodily consequences of a movement become associated to motor representations coding for that actual movement [8]. The planning and control of actions becomes anticipatory as it is driven by the desired sensory situations or desired action effects.

Forward models represent a computational models that take into consideration all these new concepts. Mainly investigated in the field of motor control, a forward model is an internal model which incorporates knowledge about sensory changes produced by self-generated actions of an agent. As shown in Fig 1, given a sensory situation $S_t$ and a motor command $M^*_t$ (intended or actual action) the forward model predicts the next sensory situation $S_{t+1}$.

![Figure 1. Forward Model](image)

Forward models provide an alternative to the classical approaches mentioned on Section 1.1. Möller [11] suggested forward models as a possibility to integrate visual perception and action generation.

Using artificial autonomous agents, anticipation and forward models can be used as a base for coherent behaviour. As mentioned in Section 1 (autonomous) agents interact with their environment in a direct way where, prediction of events represents a highly valuable capability.

It has been shown that an anticipatory agent, learning and using a forward model should be able to have sufficient information to avoid undesired situations, reacting timely to the hazards of its environment [9], [10].

Very interesting results have been presented by Dearden et. al. [3] where a robot learns a forward model that successfully imitates actions presented to its visual system. Hoffman et. al [6], [5] presented a chain of forward models that provides an agent with the capability to select different actions to achieve a goal situation and perform mental transformations. A form of anticipation is presented by Ziemke et. al [17], that without being called a forward model, incorporates several aspects of the ideomotor theories.

1.3 Bayesian Reasoning

2 Proposed Model

2.1 Forward Model

The forward model is obtained by training an artificial neural network with data coming from a simulated agent, the network is then tested on trajectories not seen during training.

Using a simulator a robot is placed in a 2D arena where the unit of measure is the pixel. The robot collects data as it moves in straight trajectories, consisting of:

- Visual information. Coming form a linear omnidirectional camera, the robot takes $360^\circ$ snapshots of its world every 20 pixels.
- Tactile information. Coming from simulated bumpers, the robot senses at every step whether it has crashed or not.

A system is needed that is able to predict visual information as well as the simulated bumper states. This system is implemented as a forward model of the form seen in Figure 2, where the current sensory situation is composed by the visual images $V$ at times $t$, $t+1$ and $t+2$. This form of the input is expected to provide the model with the necessary information to learn the temporal structure of the data. We claim that even though the motor command is constant, the displacement of the agent is still encoded in the visual data as an action. The output of the forward model is the visual scene and the bumper state for time $t + 3$: this is, $V_{t+3}$ and $B_{t+3}$ respectively.

![Figure 2. Particular Forward Model](image)

The system is implemented to perform local symmetrical predictions. This is implemented as a set of forward models each of them taking its input from a section of the sensory input and preding only the central pixel of that section. On the edges of the image this is not possible, so the input window is shifted in order to use the available information.
Given that the final size of the images is 50 pixels, the system consists of 50 networks, multi-layer perceptrons trained with Resilient Back-propagation. Each network has a size of 45 input units (15 pixels for each time step), 10 hidden units and 2 output units, one for the predicted pixel and one for the predicted bumper value (0 for no collision and 1 for collision).

Training patterns for each network are prepared consisting of several images (46000 patterns) with a mixture of different collisions and collision-free trajectories. These trajectories are straight trajectories with randomly positioned obstacles. When there is no collision the trajectory consists of 80 steps, when there is a collision the trajectory ends at the moment of the crash.

It is important to note that the model learns a association between visual and tactile stimuli. This multi-modal representation together with the known covert or overt action can be categorized as an event in the framework provided by TEC [7]. For the details of the implemented model see [9], [10] where it is shown that the bumper activation values provide information about the future location of obstacles.

2.2 Bayesian Controller

The forward model does a sensory prediction based on the actual sensory situation \( S_t \) and a covert motor command \( M^*_t \). The predicted sensory situation \( S_{t+1} \) provides the agent with the capability to decide whether the execution of that motor command is safe.

At the same time the bayesian controller takes the actual sensory situation \( S_t \) and a desired collision free sensory situation \( S'_{t+1} \) to produce a motor command \( M'_t \).

Based on the predicted sensory situation produced by the forward model the agent takes one of the two motor commands, either the one covert motor command used by the forward model \( M^*_t \) or the necessary motor command to produce a collision free situation \( M'_t \) suggested by the bayesian controller.

This architecture uses two different types of knowledge, on the one hand the forward model is learnt through the interaction of the agent with its environment. On the other, the bayesian controller represents basic a priori knowledge the agent has about its world.

2.3 Hybrid Architecture

The work presented in this paper attempts to provide an artificial agent with the necessary tools to navigate safely in an environment that contains obstacles. This is achieved through the interaction of two modules, a forward model and a bayesian controller interacting as it is shown in Fig 4.

The prediction the agent performs is based on the motor-visual inputs to the forward model. This prediction is formed by multi-modal sensory representations composed of visual and tactile stimuli.

The association formed by the input and the prediction of the forward model can be thought of as an event composed by the motor command and the sensory situations (actual and desired) [7].
References


