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Forming Goal-directed Memory for Cognitive Development

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I. INTRODUCTION

A. The Challenge of Skill Acquisition

Cognitive development [1] gives rise to the major challenge of skill acquisition, *i.e.*, the learning of a new physical skill for object manipulation. This learning is very difficult because the system designer cannot specify *a priori* all the necessary robot actions depending on the latest states of objects and environmental conditions. Even slightly different environments or facing new objects lead to an undesirable re–programming of the action programs of the robot.

B. Related Work

At the perceptual level, approaches to skill acquisition are imitation learning and coaching. Researchers created an imitation learning system [2], [3] controlling a humanoid robotic hand. Their imitation system learns hand postures by observing the hand of a human with a camera. Their imitation system uses a higher order Hopfield network (HHOP) as the main mechanism. In [3], Chaminade *et al.* showed that the HHOP was able to generalize between the learned patterns to a limited extent, *i.e.*, it could generate a few new gestures correctly even though they were *not* trained *a priori*. On the way from the perceptual level to motor control, system designers have to deal with object manipulation. In embodied cognition, objects are represented by sensorimotor patterns to reduce the symbol grounding problem [4]. Wörgötter *et al.* introduced their concept of object–action complexes [5] to describe possible actions, which a robot can perform on a given object.

C. Our approach

Our long term goal is the creation of a new cognitive architecture for skill acquisition. A cognitive architecture [6] is fundamental to any intelligent robot. In this paper, we present a first part of our future architecture. That part is based on our idea of *meaningful associations*. So far, a meaningful association is the link between a given percept, a learned goal state, and a corresponding action leading to that goal state, similar to the concept of object–action complexes. But at a later developmental stage, a meaningful association also includes cross links to abstract values (*good* or *bad* percepts / actions) and memories, which bias the current actions of the robot. For these associations, we do *not* provide *a priori* symbolic knowledge at all, instead we put the emphasis on the close interaction between the robot, its local sorrounding, and its human coach. A human coach shows the robot these meaningful associations by giving tactile feedback. Through continuous interaction with objects and a coach, the robot increases the amount of such associations, representing an increase of knowledge. Knowledge is internally stored by forming goal–directed memory contents. So far, these contents ground themselves in associations between sensorimotor and neural patterns, representing percepts, goals, and goal–directed actions (later, also values). Our approach has the potential to exploit many cross–modal associations, *e.g.*, visual, tactile, which can in turn bias the behaviour of the robot in a useful manner. Therefore, we developed the foundations [2], [3] in the following ways:
As a part of our cognitive architecture, we created a perception system with goal–directed memory to trigger goal–directed physical actions of the robot (a Humanoid Robot NAO). Our perception system processes latest visual data, enables visual servoing, and influences the behaviour of a robot by using previous experiences stored in an episodic memory module. The episodic memory is implemented by Hopfield networks. First, in contrast to [2] and [3], we extend the feature space of the Hopfield networks in order to capture not only simple shapes, but also basic colours. Second, we combine the memory output with a pattern associator, in order to link a recalled percept to a learned goal state. This goal state can in turn trigger a corresponding goal–directed action of the robot resulting into a new percept.

II. SYSTEM DESCRIPTION

A functional diagram of our perception system with goal–directed memory is depicted in Fig. 1. The sensor modalities of our system are vision and tactile feedback. However, the main modality is vision using any colour camera built into a robot. Tactile feedback only initiates the storage of the latest percept into the episodic memory. We implemented several fields of simple receptive cells, each responsive to certain visual features, such as shape, contour, and colour. Currently, we use four types of simple receptive cells, so called *simple retina cells*, as well as higher level receptive cells. Simple receptive cells are sensitive to shape and contour, mainly of objects in the foreground, and to each of the basic colours red, green, and blue. Each of these cells corresponds to a bipolar neuron, *i.e.*, it fires (activation value $+1$) when a certain feature is present, or it does not fire (activation value -1) when the feature is absent. A higher level receptive cell is only active, when both a shape cell and a corresponding colour cell are active at the same time. We implemented a simple, but robust and flexible visual servoing module, which directs the head of the robot towards an object of interest. Our visual servoing

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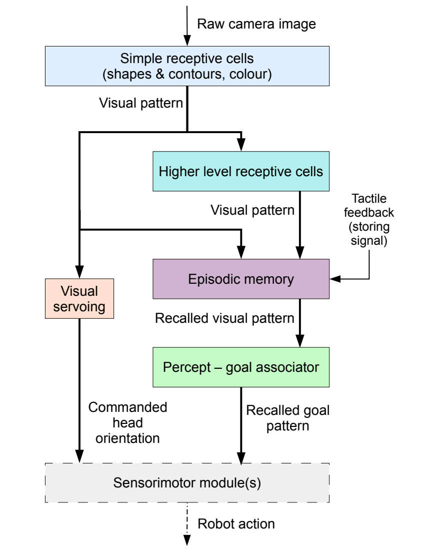
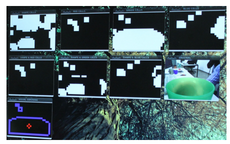


(a) Perception system with goal–directed memory.

(b) NAO robot memorizes meaningful percepts by a tap on its head.



(c) Display of the current state of simple cells (first row) and higher level cells (second row), as well as visual servoing (bottom left) at the time when photo 1(b) was taken.

Fig. 1. Our perception system with goal–directed memory, depicted in functional diagram 1(a). Simple receptive cells emulate bio–inspired vision. Visual servoing directs the head of the robot to an object of interest, *e.g.*, a green cup. A human coach guides the learning by giving tactile feedback, see fig. 1(b). Tactile feedback activates the storage of visual patterns through the episodic memory. The percept–goal associator links a recalled visual pattern to a goal, which in turn triggers goal–directed actions of the robot. Goal–directed actions are realized by sensorimotor modules. During an executed action, the system is in a closed loop with its environment, and open to new (recalled) percepts and tactile feedback. These can influence the executed action at any time.

module moves the robot head, so that the object is in the middle of the field of view of its camera. Here, an important aspect is to note that at this stage, our perception system does *not* regard an object as an object. Our overall system will bootstrap this skill of higher level categorization at a later developmental stage, after enough interactions between the robot and environment have occurred. The activation signals from the simple as well as higher level receptive cells run into the episodic memory module. The storage of percepts is triggered by tactile reinforcement on the robot through a human coach. The episodic memory uses either the classic Hopfield network [7], or the higher order Hopfield network (HHOP) presented in [2], [3]. The drawback of the HHOP is its huge need of computer memory (given N neurons, then N^3 weights need to be saved, compared to N^2 weights in a classic Hopfield net). However, the advantage of HHOP is its limited ability to generalize to new patterns based on the already learned ones [3]. The episodic memory recalls a known visual pattern, *e.g.*, of an object the robot has experienced before. The percept–goal associator links an abstract goal (*e.g.*, *lift the object up*) to that recalled visual pattern by using a feedforward neural network. The goal state is represented by a neural pattern, which self–emerges through the interaction with a human coach. In sum, once the robot sees an already known object, our perception system recalls a visual pattern representing that object. The recalled visual pattern is in turn associated with a suitable goal (affordance, *e.g.*, *lift the object up*) enabling the robot to initiate action programs leading to that goal.

III. Results

Our perception system is a part of our new cognitive architecture and is still an ongoing project. The simple and higher level receptive cells as well as the visual servoing module are fully implemented. So far we focused only on that part of the episodic memory, which responds to shape and contour. Within that part, we compared the classic Hopfield and higher order Hopfield network (HHOP) performance. We validated that the classic Hopfield network as well as the HHOP are not sufficient for usage as an episodic memory for a cognitive architecture when only the feature of shape and contour is considered. This is due to the consideration of only one feature (shape respectively contour) on the one hand, and to memory interferences on the other hand. We showed that the addition of colour features enhanced their performance by increasing the dimensionality of the overall stored pattern. Like Chaminade *et al.* [3], we observed that new patterns emerged within the higher order Hopfield network, which were *not* stored previously. All the implemented modules of our system run successfully on a NAO robot according to the descriptions in part II.

IV. Conclusion

We presented a perception system with goal–directed memory forming an important part of our cognitive architecture. Our perception system uses basic visual features and relies on tactile feedback given by a human coach to create meaningful associations between percepts and goals triggering goal–directed actions.

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