

Sensory-motor coordination: the metaphor and beyond

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Abstract

Any agent in the real world has to be able to make distinctions between different types of objects, i.e. it must have the competence of categorization. In mobile agents, there is a large variation in proximal sensory stimulation originating from the same object. Therefore, categorization behavior is hard to achieve, and the successes in the past in solving this problem, have been limited. In this paper it is proposed that the problem of categorization in the real world is significantly simplified if it is viewed as one of sensory-motor coordination, rather than one of information processing happening “on the input side”. A series of models is presented to illustrate the approach. It is concluded that we should consider replacing the metaphor of information processing for intelligent systems by the one of sensory-motor coordination. But the principle of sensory-motor coordination is more than a metaphor. It offers concrete mechanisms for putting agents to work in the real world. These ideas are illustrated with a series of experiments.

KEYWORDS: Sensory-motor coordination — categorization — autonomous agents — learning

Introduction

The field of “New Artificial Intelligence” (“New AI”), which includes the approach of “real-world autonomous agents”, promises to shed new light onto hard problems in the study of intelligence. One core assumption of this approach is that intelligence must be studied in the context of system-environment interaction. The concept of *sensory-motor coordination* presented in this paper is an attempt to apply the New AI perspective to the problem of *categorization* by capitalizing on the system-environment interaction.

What do we mean by categorization? In most textbooks categorization is defined in terms of mappings of sensory stimulation onto internal representations (e.g. category nodes). Many psychological models of categorization, for example, consist of an input layer that codes the object features and an output layer that represents the categories (e.g. [13]). Typically, the goal is to learn - via supervised learning schemes such as the delta rule - an association or mapping between activations in the input layer and the corresponding activations in the category layer. The same principle also underlies more elaborated models such as ALCOVE (e.g. [15]) where in addition to an input and an output layer a hidden layer is used. Postulating

internal representations. however, has been shown to lead to many conceptual problems (e.g. [5]). Thus, in this paper we want to define categorization in purely behavioral terms.

Let us take an example. We observe an infant picking apples from a table, while leaving the newspapers. We say that his behavior is based on a category that we might want to call “apple”. Note that this is an attribution made to the infant by an observer. Moreover, it is an attribute of the infant as a whole, not of one part of the infant, say its brain. We do not have to postulate any kind of representation in order to describe its behavior. Thus, if an agent consistently displays one kind of behavior when it encounters one type of object but not when it encounters other objects, it is reasonable to talk about categories of the agent.

If an infant initially picks different kinds of things off the table and over time only chooses apples, we say that it has learned the category that we call “apples”. Again, learning is attributed by the observer to the agent as a whole. We observe a change in his behavior over time: the agent begins to consistently show certain behaviors in reaction to objects that he did not exhibit before. Again, we are not talking about internal representations whatsoever.

How this change comes about, is an entirely different story. It is one of the main goals of this paper to propose mechanisms that will make the agent behave in a way that we as observers might want to call categorical. It is then of interest to correlate behavior and internal mechanism in order to further our understanding of how this behavior comes about. Hopefully this will also shed light on the question of what we might want to call a representation.

Categorization of the type just described is fundamental to adaptive behavior. Animals need to discriminate between food and non-food, they must recognize the nest, and they have to differentiate between conspecifics and individuals of other species. A robot for collecting garbage has to be able to distinguish between garbage and non-garbage, the garbage truck from other trucks, other garbage robots from human agents, it has to be able to recognize the charging station, etc. This competence is called *classification* or *categorization*. Some aspects of this capacity can be innate or pre-defined such as the taste of particular foods or the recognition of conspecifics. Others, like the shape of the food items and their location, might vary greatly, depending on the kind of environment. While a garbage robot might have a predefined way of identifying the charging station or of recognizing the garbage it should collect once it is nearby, the location of the charging station, or the visual appearance of the garbage might vary from city to city.

How do we endow our robots with the capacity to categorize? One way is to predefine the categories by either incorporating a special sensor (e.g. for color or conductivity), another by predefining configurations in sensory space that correspond to various categories. While the former is easily achievable, we do not gain many insights into the nature of intelligence. The latter turns out to be difficult, especially if we take into account that the agents move around and that one and the same object leads to a large variety of proximal stimulation of the sensors. By proximal sensory stimulation we mean the actual stimulation of the retina or other sensors. Although in simple environments predefining activation patterns might still be possible, it will no longer work in a general sense in more complex ones. Therefore, we want our robots to *learn* the categories. Because of our interest in intelligence, we want the agents to learn from their own perspective.

We start by discussing and motivating in detail the metaphor of sensory-motor coordination. We present some evidence supporting its importance, point out the main functions it serves, and discuss the essential implications. This is followed by the presentation of a series of models which implement this concept in a mobile robot. These models, called SMC models (for Sensory-Motor Coordination), illustrate how the problem of categorization in autonomous agents can be approached by capitalizing on the system-environment interaction. The models are tested in a robot that has to solve a collecting task. Because there

are several types of objects in the robot's environment, it has to learn to discriminate between objects it should collect and other objects it should avoid.

For each model, we start with the ecological niche and the task, the architecture, and the individual processes that make up the architecture. A series of experiments is then presented. They are designed to illustrate the relation between the sensory-motor stimulation and the behavior of the agent, the evolution of the learning process, and the development of the categories, as seen in the agent's behavior. In the discussion section we include a number of design principles that can be extracted from the studies presented. We conclude by pointing out the limitations of the current models and indicate directions for further investigation.

Sensory-motor coordination

There is a large body of literature on categorization in a number of disciplines like psychology, connectionism, computer vision, and human and animal vision in neuroscience. Most of the work in cognitive psychology does not pertain directly to our problem. In the experiments, typically, adults are tested on static images. The models developed on this basis (exemplar, prototype, decision bound, etc., see e.g. [3]) can therefore not be employed for our mobile agents because mobile agents are exposed to a continuous stream of ever-changing sensory stimulation.

A similar argument holds for most of the work in connectionism and in computer vision. Normally, a static image, a snapshot, is taken from an array of sensor readings, e.g. from a CCD camera. This image is transmitted to a central processor. Algorithms are applied to it with the goal of extracting the objects, or, in other words, of mapping the pixel array onto an internal model. While this approach has been successful in industrial robotics where a lot is known about the environment, the types of objects, and the spatial relationships, it has not been very successful for mobile robots. Because the sensory or proximal stimulation depends strongly on distance and orientation, it turned out to be extremely difficult to perform the mapping onto an internal model. In spite of the enormous efforts that had been put into computer vision, the problems remained (e.g. [31]).

These considerations led ourselves and others to the conclusion that a radically different approach is needed. We propose that it consists in viewing categorization as a sensory-motor coordination. This contrasts strongly with traditional thinking. For example, virtually all models in cognitive psychology on the topic, including prototype based, exemplar based, or decision bound models, endorse an information processing view of categorization. This is also—quite obviously—true for computer vision, as the term indicates: computers process information. The approach can be characterized as follows: an input is presented to the agent, this input is transmitted to and processed by a central processor, and finally an action is generated. This separation of input, processing, and output, leads to a number of fundamental problems (e.g. object invariance, real-time behavior, homunculus problem). As a consequence, it has been criticized in a number of disciplines. In what follows we focus on the neurobiological, psychological and computer vision literature related to the problem of perception and categorization.

The underlying idea is best illustrated by a quote from the American philosopher and psychologist John Dewey ([7]) who recognized the problem a long time ago and has provided inspiration for our work¹. Dewey first presents the standard view that starts from sensory stimulation, goes on to internal processing and finally generates an action. Here is the alternative he suggests:

“We begin not with a sensory stimulus, but with a sensorimotor co-ordination ... In a certain sense it is the movement which is primary, and the sensation which is secondary, the movement of the

¹We are grateful to Bill Clancey for drawing our attention to the work of John Dewey who has pointed out many of the relevant problems more than a century ago.

body, head, and eye muscles determining the quality of what is experienced.” (Dewey, 1898, pp. 137-138)

In *neurobiology*, Edelman ([9]) has been discussing categorization from a similar perspective, by outlining the sensory-motor areas that are involved in categorization. Douglas et al. ([8]) suggest that vision should not be viewed as passive information processing but rather as an active "integrated sensorimotor event" encompassing the various oculomotor circuits.

In *developmental psychology*, experiments with infants suggest a similar view of categorization, namely one in which sensory and motor components are equally important. The work of Thelen and Smith ([30]) draws on Edelman's theory of reentrant mappings. It strongly supports the view of categorization as sensory-motor coordination.

“The key notion here is that the global functions of categorization—memory, learning, and performance—arise dynamically from the reentrant mapping of motor activity along with sensory information from many modalities. More specifically, in early development, movement and sensory signals are completely coupled and act together to form the global maps that are the basis of further development ...” (p. 160).

More recent approaches to *computer vision*, in particular animate vision (e.g. [2]), include an important aspect of sensory-motor coordination, namely motion of the head and the eyes. They do not (yet) include the agent's ability to move around and in fact manipulate the objects directly.

So far we have reviewed evidence from various fields, psychology, neurobiology, and computer vision (animate vision), demonstrating that sensory-motor coordination is important. But what are the reasons behind it? Why is it so ubiquitous? The answer is that it serves several key purposes.

(1) It provides the basis for *physical control over objects*. Needless to say, having control over objects like food items or building materials has many advantages for survival and has therefore a strong functional character. This type of sensory-motor coordination has been found to be important in infants' discovery of an object's 3-D structure (e.g [24]). Infants generate the visual information necessary to detect the 3-D structure of an object by rotating the object held in the hand. It has been found that inspections of objects held in the hand are also conducted at a close distance, which means that the objects are unlikely to be occluded by other objects; hence, there is less ambiguity regarding their full contours than if the same objects are viewed from a large distance. Moreover, the relatively constant distance from which hand-held objects are viewed makes real size relationships readily apparent. In sum, the visual information related to an object's 3-D structure is especially clear and accessible when the object is viewed while held and maneuvered in the hand, i.e. as the infant has physical control over the object.

(2) A second purpose is of a *perceptual nature*: sensory-motor coordination implies that both sensory and motor processes play an integral part in perception. From this it follows that in ontogenetic development the two should co-evolve since otherwise a there could be no coordination. For robots this means that sensory and motor abilities should “match” in complexity, i.e. they should obey the principle of ecological balance ([23]). The same principle can again be observed in infants. It has been found that very often infants must have certain motor capabilities before the corresponding perceptual abilities can emerge (e.g. [6]). For example, there is a clear correspondence between the development of both haptic and depth perception with the onset of particular motor abilities.

(3) The third purpose is more of an information-theoretic nature: sensory-motor coordination *induces correlations*, thus reducing the high dimensional sensory-motor space to a low-dimensional sub-space. These correlations are largely due to the agent's self-motion. They are essential enablers of categorization and learning and provide a natural focus-of-attention mechanism.

(4) It allows for the *integration of several sensory modalities* (e.g. visual, haptic, or auditory). This can be achieved by forming associations according to spatio-temporal correlations that exist between various

sensory modalities. An example of a learned visuo-haptic association will be presented below. Thus, sensory-motor coordination has an exploratory function: new relationships can be discovered. Again, this principle is found in infant research.

(5) And finally the most obvious purpose of sensory-motor coordination is learning to master sensory-motor coordination itself, e.g. hand-eye coordination which is essential in reaching and grasping behavior (e.g. [16]; [20]). This can be learned from the correlation of sensory signals produced by self-motion.

In sum, sensory-motor coordination serves fundamental purposes for the perception of both natural and artificial agents. Each of these functions will be discussed in more detail below. They have been incorporated in the SMC models.

The SMC Models

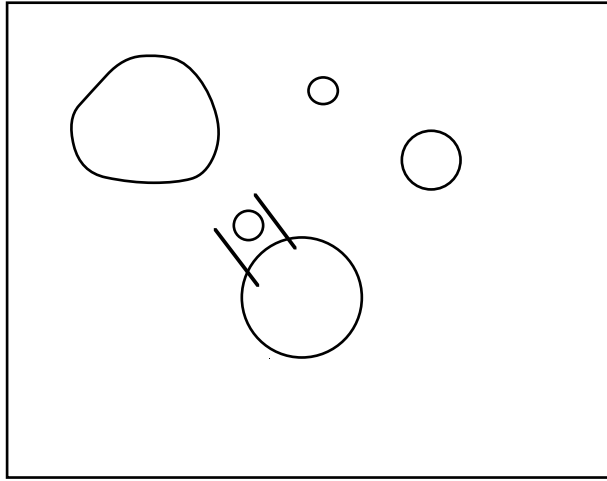
We will now design a series of models which we call the SMC models. They implement the concept of sensory-motor coordination on various levels. The task of these agents is to learn to collect some types of objects (e.g. small ones) while ignoring others (e.g. large ones). In order to solve its task the robot has to be able to make distinctions between the various types of objects. SMC Ia and SMC Ib are first attempts to equip a robot with the ability to categorize based on the notion of sensory-motor coordination. After extensive experimentation with these models it turned out that they have certain deficiencies. We report them here because the deficiencies are equally important as the achievements in terms of what we can learn from them. They also motivate the next model, SMC II. This model is implemented on a robot with a more complex sensory-motor setup, including a CCD camera. Moreover, the categorization mechanisms are different from the ones used in the SMC I models. Finally, SMC III will be briefly introduced. This model runs on a robot which can operate outdoors. It is a first step towards the overall goal of building a garbage-collecting robot. The main aim in this paragraph is not so much to explain each and every detail of the individual models but rather to illustrate the power of the metaphor of sensory-motor coordination in generating productive ideas which can be tested on robots or in experiments with natural agents.

SMC I: Learning sensory-motor mappings

Ecological niche and task.

Whenever designing an agent, we first have to specify the ecological niche and the tasks. The morphology and the whole set-up of the agent largely determine the ecological niche and the potential tasks it can perform. For the experiments described below we have been using a miniature robot, Khepera™. It has small wheels, so its econiche is restricted to flat, clean surfaces. The kinds of tasks are also restricted by the sensory-motor set-up. We have used the 8 IR-sensors, the ambient light sensors, and a gripper with two degrees of freedom. Instead of different types of garbage, there are objects of different sizes in the environment. The agent has to bring the small objects to location A (with a light source), leave the large ones where they are, and it has to push the objects of intermediate size to a wall. This is illustrated in figure 1.

Thus, there are three different types of behaviors the agent should engage in depending on the nature of the object it encounters.



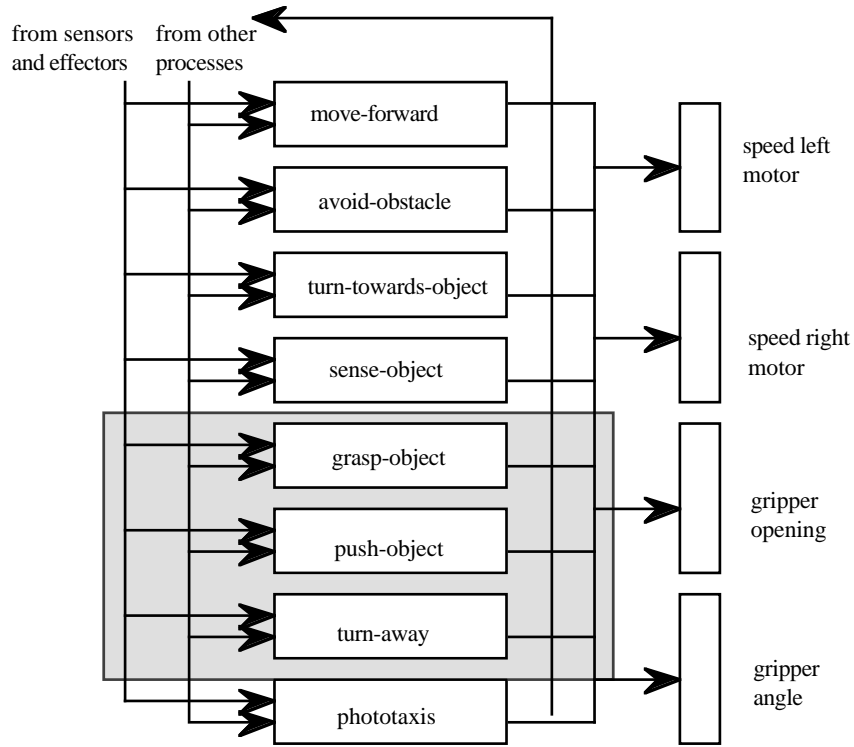


Figure 2: EBA agent architecture. The shaded area is explained in more detail in figure 4. Explanations, see text.

Description of processes

In the EBA architecture, all processes are in principle active all the time and continuously write onto the motor variables of the wheels and the gripper, and possibly onto additional variables. Formally this can be expressed as follows:

$$\mathbf{s}(t) = (s_l(t), s_r(t)) = \left(\sum_{i=1}^N o_i^l(t), \sum_{i=1}^N o_i^r(t) \right) \quad (1)$$

where $s_l(t)$ and $s_r(t)$ are the left and the right motor speed, $o_i^l(t)$ and $o_i^r(t)$ the contributions of process i to the motor speeds, and N is the total number of processes. A similar relation holds for the gripper variables:

$$g^\alpha(t) = \sum_{i=1}^N g_i^\alpha(t) \quad (2)$$

where $g^\alpha(t)$ is the angle of the gripper (see figure 3) and $g_i^\alpha(t)$ is the contribution by process i .

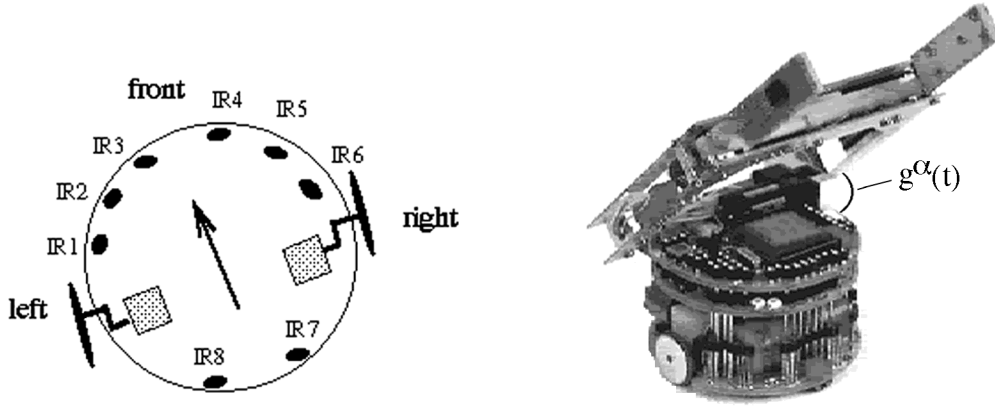


Figure 3: Schematic representation of the robot. Top view on the left, side view with gripper on the right.

Given this architecture, the behavior of the agent is emergent from the dynamical system of motor variables, rather than being the result of an action selection mechanism.

A short overview of the processes has been compiled in box 1. A schematic representation of the robot is shown in figure 3.

Box 1: Processes implemented on the agent

For some of the processes, the formal descriptions of their implementation are given for the purpose of illustration.

- *move-forward*: if there is no significant stimulation of any IR sensors, move forward. *Intuition*: if there is no significant sensory stimulation in the IRs (the proximity sensors), this is an uninteresting situation. Moving forward will increase the chance of encountering an object of potential interest. Formally, *move-forward* can be described as follows:

$$o_{mf}^l(t) = o_{mf}^r(t) = 1 - \frac{IR_3(t) + IR_4(t)}{2} \quad (1.1)$$

where $o_{mf}^l(t)$ and $o_{mf}^r(t)$ are the outputs of the left and right motors, and IR_i are the current readings of the two front IR sensors.

- *avoid-obstacle*: if there is stimulation in the front sensors, turn to the side. *Intuition*: don't hit obstacles in order not to get damaged. Formally, we can write:

$$\begin{aligned} o_{ao}^l(t) &= \sum_{i=1}^3 \phi_i IR_i(t) - \sum_{i=4}^6 \phi_i IR_i(t) \\ o_{ao}^r(t) &= -\sum_{i=1}^3 \phi_{6-i+1} IR_i(t) + \sum_{i=4}^6 \phi_{6-i+1} IR_i(t) \end{aligned} \quad (1.2)$$

where ϕ_i is a parameter determining the influence of each corresponding IR sensor on the output of the process. Obstacles on the right will lead to large values in the sensors on the right side and thus to an increase of the speed quantity associated with the left motor and a decrease of the speed quantity associated with the right motor.

- *turn-towards-object*: if there is lateral stimulation in a sensor, turn slightly towards that object. *Intuition*: objects are more interesting than open spaces. This reflex ensures that the agent has a tendency to be near objects, thus increasing the probability for an interaction of interest. Moreover, in the interaction with the avoid-obstacle process this leads to a particular sensory-motor coordination (see text).

$$\begin{aligned}
a_{ito}^l(t) &= IR_l(t) - [IR_l(t-1) - a_{ito}^l(t-1)] \\
a_{ito}^r(t) &= IR_r(t) - [IR_r(t-1) - a_{ito}^r(t-1)] \\
o_{ito}^l(t) &= \tanh(2.5 * a_{ito}^l(t)) \\
o_{ito}^r(t) &= \tanh(2.5 * a_{ito}^r(t))
\end{aligned} \tag{1.3}$$

where IR_l is the sensor on the left, IR_r the one on the right (see figure 3).

- *sense-object*: if there has been lateral stimulation over some period of time, determine the “type” of object (graspable, pushable, to-be-avoided) (details, see text). *Intuition*: different types of objects should lead to different behaviors.
- *grasp-object*: if the sense-object process delivers a graspable object, grasp it (i.e. pick it up). *Intuition*: grasping is the most interesting form of interaction with the environment.
- *push-object*: if it encounters a non-graspable object that is not too large to fit between its hands: push it against the wall. This information is delivered to the agent by the *sense-object* process. Note that in this case, the avoid-obstacle process is still active, so the agent will turn a bit to the side. Since the hands of the gripper are around the object, it will not lose it and it will move forward because it received a lot of activation from the sense-object process. *Intuition*: This process applies whenever the sense-object process senses an object that is “too heavy”—pushing is the next best behavior to picking up the object.
- *turn-away*: if the sense-object process does not yield an object between the hands: turn away. *Intuition*: turn away from uninteresting objects, i.e. objects which do not fit in the gripper.

In a complete architecture for a self-sufficient agent, we would have to include processes for recharging. In order not to overload the presentation of the sensory-motor issues, we have left the self-sufficiency part out of the current discussion.

SMC Ia: Value-based learning

In order to guarantee survival, physical integrity, and task performance of any agent, a value system has to be predefined by the designer. It includes basic reflexes, basic reinforcers, and reinforcement learning schemes. All the reflexes have been implemented as Braitenberg-style processes. Examples are move-forward, avoid-obstacle, and sense-object. The basic reinforcers have been defined by analogy to biological systems. If the agent has been successful at grasping an object, this is considered intrinsically rewarding and a signal is generated by the value system. The same holds for pushing large objects and avoiding very large ones. The value signal thus generated influences the learning process (see figure 5).

With these concepts in mind we can define two types of learning, namely *value-based* learning and *exploration-based* learning. Learning is called value-based if it is driven by the explicit reinforcement signals of the basic value system. The first of the SMC models described here, SMC Ia, implements value-based learning. Learning is called exploration-based if it takes places during exploration. It is not driven by explicit value signals. Exploration means, for example, circling around an object or rotating an object with the gripper in order to get different views. Exploration-based learning is implemented in model SMC Ib (see below).

The intuitions are as follows. Picking up objects and pushing objects are what the agent is supposed to do. They are therefore associated with intrinsic value. Avoiding very large objects also has value, because the agent is prevented from engaging in useless behaviors, i.e. behaviors that are not associated with value.

Let us now look at what an agent with the architecture of figure 2 will do. Normally, it will move forward (“move-forward” process) and when encountering an obstacle, it will avoid it, i.e. it will turn away (“avoid-obstacle” process). At the same time, if there is stimulation in one of its lateral (left or right) sensors, it will turn slightly towards the object (“turn-towards-object” process). The interaction of

the “avoid-obstacle” and the “turn-towards-object” processes leads to a behavior that we might want to call “move-along-object”. This is a form of sensory-motor coordination: sensors and motor actions are coupled via the two reflexes.

This coupling fulfills one of the functions of sensory-motor coordination mentioned earlier. It leads to correlations in the activation levels of different sensor modalities, namely the wheel encoders and the IR sensors. Another way of saying this is that the activation levels are *time-locked*. These correlations imply temporally stable patterns in a subspace that has significantly lower dimensionality than the entire sensory-motor space. This low dimensionality is one of the important reasons why sensory-motor coordination is essential for categorization. This point will be illustrated in the experiment section.

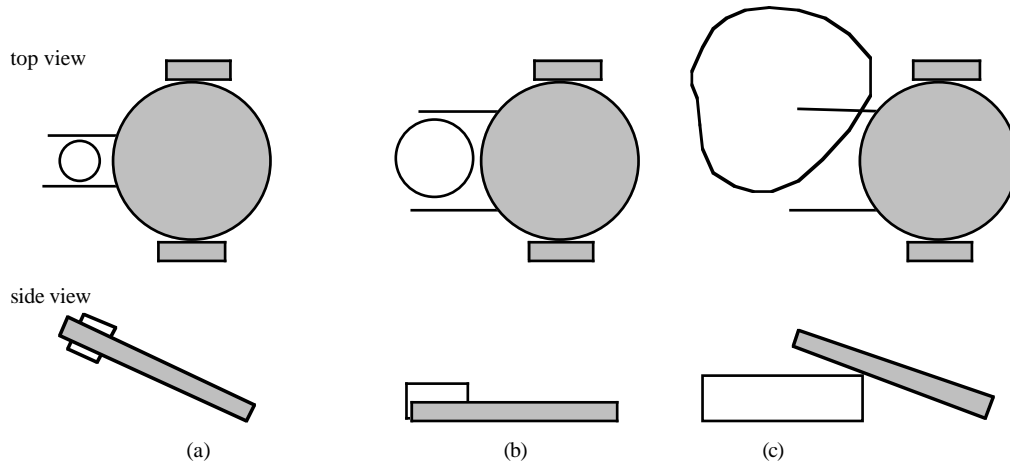


Figure 4: The different results of the “sense-object” process. (a) a small, liftable object, (b) an object of intermediate size that can be taken between the hands of the gripper, but not lifted, (c) a large object—the gripper cannot be lowered over the object.

After the agent has moved along an object for some time, i.e. after it has had continuous stimulation of a lateral sensor, a reflex is triggered: it enables the agent to find out what it can do with the object (“sense-object” process). Sense-object consists in lowering the gripper over the object. It will first try to grasp it (“grasp-object” process). If the object is graspable and the agent can pick it up (figure 4a), a reinforcement signal is generated which reinforces the association between the sensory-motor sequence the agent has been engaged in right before grasping and the grasp process (a neural network that implements the grasp process). The part of the architecture responsible for learning is depicted in figure 5. If the agent has successfully grasped a peg it will bring the object to a home station by means of a phototaxis process.

If the object is too heavy it cannot be picked up and the agent will try to push it (“push-object” process). If it is successful (figure 4b), a reinforcement signal for associating the sensory-motor sequence before the pushing and the neural network of the push process is generated. If the gripper cannot be lowered over the object (figure 4c), it will turn away and a reinforcement signal for turning away is generated.

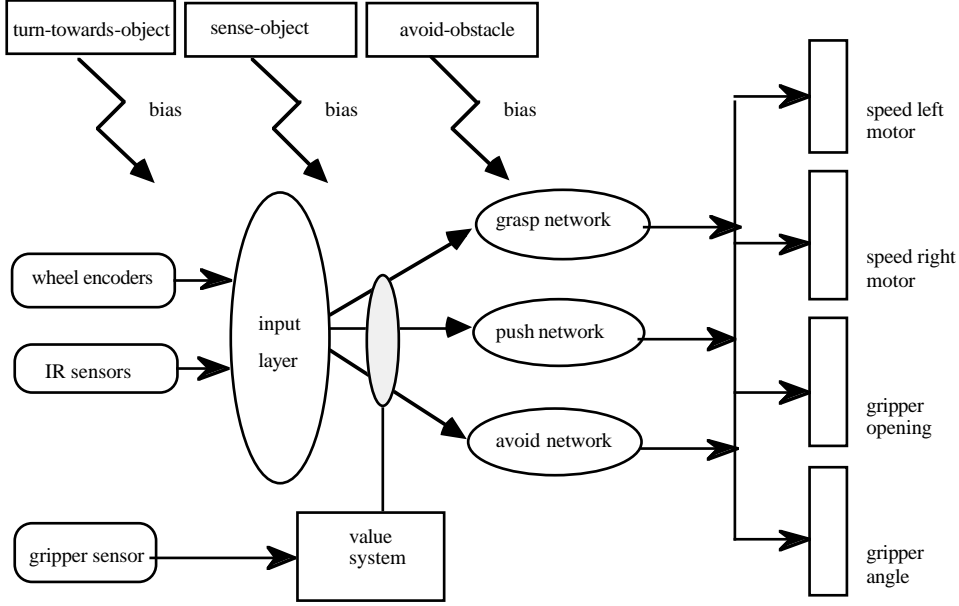


Figure 5: Details of the value-based learning scheme for the “grasp-object”, “push-object”, and the “avoid-obstacle” processes. Where we want to stress the neural network implementation, we use ellipses. Sensors are represented by boxes with rounded corners. Explanations, see text.

In order to be able to reinforce the connections between a particular sensory-motor coordination and the networks for the different processes (grasp network, push network, avoid network in figure 5), the sensor readings from the IR sensors and the wheel encoders are projected into a network layer (called the input layer) consisting of leaky integrators for all the sensor variables. This provides a certain amount of information about the agent’s recent sensory-motor past.

We use a Hebbian learning scheme with bidirectional active forgetting. The learning rule is as follows:

$$\Delta w_{ij}^p = v^p \cdot \eta \cdot a_j^L \cdot a_i^p - \varepsilon \cdot (a_j^L + a_i^p) \cdot w_{ij}^p \quad (3)$$

where Δw_{ij}^p is the change of the weights from the input layer to the process network p , v^p is the value signal generated by the value system for process p , η is the learning rate, a_j^L the activation of node j in the input layer, and a_i^p the respective activation in process network p , and ε is the forgetting rate.

This scheme implies that learning takes place when there is activation in the sensory-motor map and in one of the three networks. Whenever one is active but not the other, the connections are weakened.

If the environment does not change over time, there will be an equilibrium and the weights will no longer change systematically. There will only be small changes due to statistical fluctuations. If a new type of object is introduced, the weights will start changing again, thus modifying the behavior of the agent. If the agent no longer encounters earlier object types, it will eventually forget about them. The stability-flexibility trade-off (e.g. [14]) can be controlled by adjusting the learning and forgetting rates. This learning scheme is incremental, meaning that it will run forever—there is no distinction between a learning and a performance phase. Incrementality is an important design principle for autonomous agents, because in the real world it does not make sense to talk about training and test sets. Note that this scheme only works, if there is an appropriate reinforcer for a new type of object, i.e. if the new type of object leads to a behavior for which a reinforcer is available. We will see below, that exploration-based learning is not subject to such a restriction.

Before looking at the experiments and the results, let us look at SMC Ib, where exploration-based learning is used to solve the collecting task.

SMC Ib: Exploration-based learning

So far, all the learning has been driven by the basic “needs” of the agent. We have assumed that, for example, grasping and pushing of a garbage collecting agent are part of its basic needs. Consequently, something is learned only if a particular interaction is successful, which is characteristic of value-based learning.

We have been experimenting with another kind of learning which we have called *exploration-based*. It employs a somewhat different architecture. Rather than learning only if a reinforcement signal is generated, the process of “exploring” the object itself is considered to be intrinsically rewarding. The “sense-object” process in figure 2 is replaced by an “explore-object” process.

Developmental studies on infants demonstrate this explore behavior. Very young infants exhibit manual behaviors that are adequate for haptically perceiving temperature, size, hardness or texture (e.g. [6]; [21]). Already during this process, learning takes place. We call the neural network that results from this learning process a *sensory-motor map*. Although the resulting architecture is very similar to the one for value-based learning, the underlying ideas differ considerably.

The sensory-motor map

The term “sensory-motor map” has been chosen in analogy to Edelman ([10]). Since Edelman is dealing with the complexities of the human visual system, and we are dealing with a simple robot with only a few simple sensors and effectors, there are obvious differences. But ignoring these simplifications, some of the underlying principles are very similar.

The only change needed in the part of the architecture shown in figure 4 is that the “input layer” is replaced by a sensory-motor map. Let us now discuss how this map is formed, i.e. how learning is achieved. In the autonomous agents literature, Kohonen maps are often used for building maps. One of the reasons for their popularity is the fact that they reduce the dimensionality while preserving the topology, which simplifies many tasks, in particular learning. Note however, that the topology is only preserved, if the map has the right dimensionality, i.e. if it reflects the dimensionality of the data in the input space. Because the sensory-motor coordination induces correlations—as discussed above—a low-dimensional map will be sufficient and can thus be used for categorization.

Kohonen maps suffer from two fundamental problems if applied to autonomous agents. First, they are not incremental. In order to guarantee convergence, the learning rate and the range of the lateral influence has to be reduced. Second, the dimensionality of the map is a global characteristic and has to be chosen at the beginning once and for all. There are excellent algorithms for determining the optimal dimensionality like the topographic product ([4]), but they require that all data be known initially. However, in an autonomous agents environment, the dimensionality of the data can vary locally over time. So what we need is an algorithm which is at the same time incremental (because of the stability-flexibility trade-off) and can vary locally in dimensionality.

The algorithm we have been using that fulfills the criteria mentioned (incrementality, local dimensionality), has been inspired by Ahrns et al. ([1]), Martinez ([19]), and by Fritzke ([11]). It is called “Growing Dynamic Cell Structures”. It works on the basis of adding and removing nodes and connections, as required by the current interactions of the agent with the environment. If the types of objects do not change over time, the network structure will reach an equilibrium state. As soon as new types of objects are introduced, it will start changing again. Box 2 contains a short description of how the algorithm works.

Box 2: “Growing Dynamic Cell Structures” (GDCS)

The initial phases of the algorithm are not very interesting for our purposes, since it has to be incremental, i.e. it has to run forever. We look at it once it has been running for some time, so that it is in an equilibrium state. In order to achieve equilibrium, we must on the one hand add nodes to the network, and on the other remove some of them if they are no longer needed. If we did not do that our network would grow indefinitely (which was the case in Fritzke’s original model, see [11]).

We only outline the principles, the details can be found in Scheier ([25]). Nodes are added under certain conditions. Let us look at one example. With each node an error value is associated. This value is increased whenever for a given input, this unit happens to be the best-matching unit. The amount by which it is increased is simply the difference between the input and the weight vector of this unit. If this error value exceeds a certain threshold, a new node is added. The intuition underlying this method is that if the error gets too large the network is not capable of covering the whole input space. The newly generated nodes have to be connected to the input nodes and to the nodes in the map (i.e. the lateral connections). The algorithm also provides a means for eliminating connections if the associated nodes are no longer used. It is implemented via a decay scheme on the connections.

Learning of the lateral connections is based on a Hebbian scheme where only the connections between the most active units are strengthened, whereas all the others are decayed. The rule used has been shown to be topology preserving ([19]), which is obviously a desirable feature.

The algorithm outlined is incremental, implying that its dimensionality is determined locally. Thus the resulting manifold has a dimensionality that varies over time.

Learning the right behaviors

Just as for pure value-based learning, the agent has to learn to associate the right processes with the various categories (sensory-motor mappings). This is done with exactly the same reinforcement scheme as before. Only this time learning is easier because the categories have already been established and only the appropriate category-process connections need to be established. This association is again purely value-based, but not the categorization process itself.

Experiments

Let us now describe a series of experiments. First we will present a number of analyses illustrating the issues. Then we will investigate the two learning architectures, SMC Ia and SMC Ib.

Effects of sensory-motor coordination

In the introduction we mentioned that the agent is exposed to a continuously changing stream of sensory stimulation, which in turn depends on the agent’s current behavior. In order to get an idea about the sensory data the agent is exposed to, we had the agent move across the open plane and then approach an object. Figure 6 shows the correlations between the 10-dimensional vectors consisting of the current readings from the 8 IR sensors and the two motor speeds. The correlations were calculated as follows. A "window" of 20 time steps (150msec/step) was defined. For this window the 20x20 correlation matrix of the 20 10-dimensional vectors was computed. In other words, the correlation of the vectors at subsequent time steps was calculated. Finally, the average over all entries in the correlation matrix was taken in order to obtain a measure of how the vectors are correlated in time. High correlations indicate that subsequent

vectors are very similar. This is the case when the robot is moving along an object, i.e. when it has established a sensory-motor coordination.

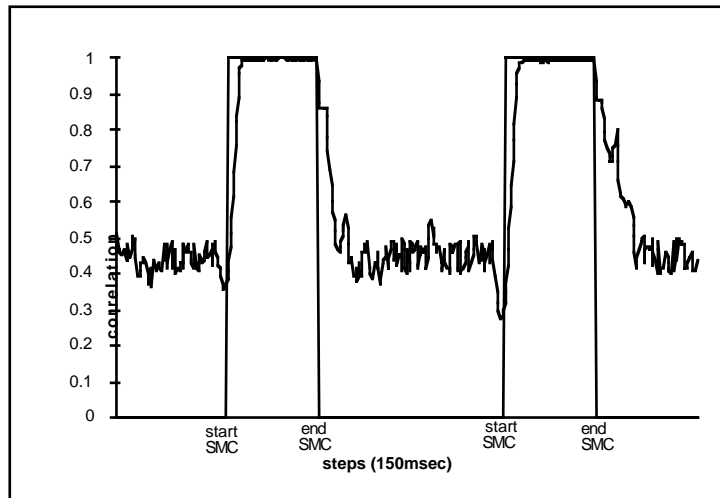


Figure 6: Change in correlations between subsequent input vectors as the agent is approaching an object. Vectors are 10-dimensional: 8 IR sensors and the two motor speeds. SMC stands for “Sensory-Motor Coordination”. The error indicates the drop in correlation as the agent approaches an object.

Figure 6 shows that the correlation is at an intermediate level as the agent moves about in the open. Theoretically, it should be one because the IR sensors have a limited range so that there would be no stimulation. The noise makes the correlations drop to roughly 0.5. The variation is due to the fact that the activation levels are low and small changes due to noise have a large effect relative to the absolute level of activation of the sensor. As the agent approaches an object, the correlation drops because now there is rapid change in sensory activation. Once the agent is near the object, the dynamics of the reflexes begins to play and we have time-locked activity in sensory-motor space. This can be seen in the correlations which rapidly jump to the maximum. Note that these correlations are induced by the agent’s own movements, or in other words, by the sensory-motor coordination.

Figure 7 illustrates the sensory data. Figure 7 (a) shows the motor speeds (dashed lines) and the resulting angular velocities (solid line). The angular velocity is simply the difference between the two motor speeds. In this example, the robot first moved in the open plane for about 40 steps. It then started to circle around a small object for about 80 steps. After it had left the object the robot first moved in the open plane again, then avoided a large object (indicated by large fluctuations around 150 and 170 steps), and finally started again to circle around a small object at around 180 steps. Figure 7 (b) displays the angular velocities (motor speeds are not shown for better visualization) for small objects (S), intermediate sized objects (I), and large objects (L). The figure suggests that the different types of objects are separable on one dimension only.

Table 1: Number of steps before engaging in appropriate behavior

SMC Ia (Value Based)	Initial	After 10 Objects
Small	40.2 \pm 1.44	14.2 \pm 1.76
Intermediate	40.8 \pm 1.42	13.4 \pm 1.84
Large	41 \pm 2.11	14.4 \pm 2.08
SMC Ib (Exploration Based)	Initial	After 10 Objects
Small	39.9 \pm 1.72	11.2 \pm 1.29
Intermediate	41.1 \pm 1.65	12.1 \pm 1.45
Large	40.3 \pm 1.78	13.6 \pm 1.59

Discussion

Let us go back to our definition of categorization and learning that we gave at the beginning. It was defined in purely behavioral terms. The behavioral data summarized in table 1 show that with both architectures, the agents learn to categorize the different types of objects. The number of steps required before the agent “recognizes” the object, i.e. starts the appropriate interaction with the object, is significantly reduced from around 40 steps to a value between 11 and 15.

The reason this works in both cases is that through the sensory-motor coordination, time-locked activation is generated in different sensor modalities, which (a) provides a focus-of-attention mechanism, and (b) reduces the dimensionality of the problem. In a sense, the invariances are *generated* through the sensory-motor coordination, rather than being “extracted”. We are not claiming that invariances could not be extracted by means of neural networks alone. What we are saying is that the neural architecture is enormously simplified if the agent’s capacity for movement is taken into account. This is an instance of the principle of “cheap design” ([22]) that characterizes intelligent agents in the real world.

In sum, the SMC I models illustrate how the metaphor of sensory-motor coordination can be used to enable an agent to reliably learn to distinguish between different types of objects. It is important to note, however, that these models are only the first step towards a better understanding of the role and use of sensory-motor coordination in natural and artificial agents. Indeed, the SMC II model incorporates important improvements which are based on many experiments with SMC I. In the course of these experiments several conceptual limitations of SMC I have come to the fore.

(1) *Predefined categories*: In a sense, it could be argued that due to the predefined value “categories” (i.e. grasping, pushing, turning away) the categories that are formed as a result of the sensory-motor coordination, are predefined by the designer (this point of criticism applies to SMC Ia, i.e. the strict value-based learning). It is correct that the categories which may *potentially* be formed is given. It is, however, open (a) which kinds of sensory-motor coordination will be associated with a category, and (b) depending on the environment not all the categories will be exploited.

(2) *Separation of category formation from value system*: One of the problems with SMC Ib is that category formation is now separate from the value system. The categories are only associated with behavior once they have already been formed. Categorization is not directly value-driven. Categories will be formed whenever there are time-locked correlations.

(3) *Limited sensory input*: One rather obvious limitation of both SMC I models is that the sensory input is limited to the IR sensors and angular velocities. In SMC II this is changed by adding a CCD camera and more complex means of proprioceptive input to the model.

In addition to these problems, several theoretical problems will be addressed in SMC II which have not been dealt with in SMC I.

SMC II: Learned reentrant mappings and attentional sensory-motor loops

Summary

The SMC II is an extension of the SMC I models. It is described in detail in Scheier and Lambrinos ([27]). Here we give a summary of the main concepts and results. In essence, the improvements consist in an increase in the sophistication of the potential sensory-motor coordinations. First, the sensory-motor complexity of the robot is significantly augmented. While the sensory system in the previous experiments consisted of IR sensors a CCD camera is now added. In addition, the control of the arm-gripper system is considerably improved. Instead of passively scanning the camera image an artificial eye has been implemented which actively moves a fovea to interesting parts (e.g. bright spots, texture, movement) of the image. This foveation process is an instance of a sensory-motor coordination. Once it has visually focused on an object the robot moves up to it and starts exploring it using the arm-gripper system. A second improvement concerns the categorization mechanisms used. In SMC I, categorization was based on (a) learning a sensory-motor mapping and (b) associating this mapping with behavioral processes (grasping, pushing, turning-away). While in SMC I there is one map, there is one for every sensory modality in SMC II. Categorization is achieved by a learned reentrant mapping between haptic and visual feature maps (see figure 8). The term reentry has been first introduced by Edelman ([9]). It refers to the fact that there are reciprocal connections between the feature maps. Reentry is necessary to account for the coordination of responses of modalities. When the robot explores an object there is visual and haptic stimulation. Reentry is a mechanism to correlate this perceptual information on the basis of their temporal contiguity. This *correlative* function of reentry has been suggested to be one of the core mechanisms for the development of categories in infants ([30]). A final extension of the SMC I framework is the concept of *attentional sensory-motor loops* (see below). “Attentional” as used here simply means that they make the robot turn towards an object of interest. As it approaches the object, the object features become more distinct and, depending on the learned categorization, the robot will either reinforce the current sensory-motor coordination or it will not be sustained. In the latter case, the robot simply ignores the object.

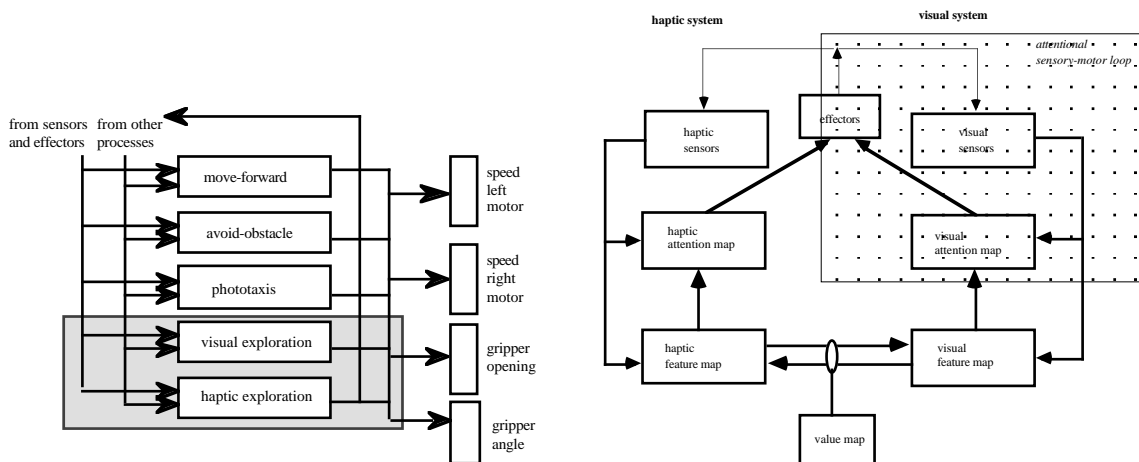


Figure 8: Overview of the SMC II architecture. There is a visual and a haptic system. Each system consists of sensory sheets, an attentional map, and a feature map. There is a learned crossmodal interaction via reentrant connections between the haptic and visual feature map. The visual attentional sensory-motor loop is highlighted on the right.

Ecological Niche and Tasks

The SMC II model was again implemented on a KheperaTM robot. As before, the task of the robot is to collect objects and to bring them to a home base. The objects were cylindrical and all of the same size. They were either conductive or non-conductive. The conductive objects had a strongly textured surface while the non-conductive ones had a white or only slightly textured surface. The robot's task was to collect the conductive objects.

Architecture

The control architecture of SMC II is again based on the EBA. In SMC II the various processes that implement object-related behavior (i.e. grasp-object, push-object, and turn-away) are replaced by two new processes: haptic and visual exploration. An overview of the haptic and visual exploration processes is shown in figure 8. This part of the model consists of a total of about 2000 units and 140'000 connections. The main ideas are as follows. We exploit the fact that the agent can interact with its environment in two ways: First, there are attentional sensory-motor loops which are directly coupled to the arm, gripper and wheel motors (i.e. the effectors of the robot). As a result the agent moves its body and the arm into a position where it can explore the object. Second, both haptic and visual data which result from the exploration process are used for learning and categorizing objects. As shown in figure 8, in both system there are sensory maps that are connected to feature maps. Feature maps respond to properties of objects such as texture (visual) or conductivity (haptic). The interaction between the two modalities is implemented via modifiable weights between these feature maps. The correlation of signals of the haptic and the visual feature maps by these reentrant connections forms the basic mechanism of categorization (provided that it is appropriately embedded into a sensory-motor system). A fundamental property of SMC II is that the feature maps are connected via modifiable feedback connections to the attention maps. The main idea is to link the correlated activity in the feature maps to the attentional sensory-motor loop. In essence, the result of learning is that relevant objects enhance activity in the attentional loop while it is not sustained in the case of uninteresting objects (in which case the object is ignored). Thus, there is no explicit avoidance or approach behavior linked to the feature maps. Instead, whether the agent approaches or avoids an object is the result of how the feature maps modulate the attentional sensory-motor loops depending on the kind of object encountered. Just as in SMC I value signals modulate the learning process. The value map receives input from the conductivity sensor and the gripper proprioceptors. The basic motivation behind these connections is that the robot should learn only when it explores an object. Activity in the value map acts like a gating function and is used as a reinforcement signal for the synaptic modifications between the feature maps.

Note that categorization in SMC II includes the agent as a whole, it is not a subsystem of some sort. Rather, the feature maps are tightly coupled to the attention maps which in turn form sensory-motor loops via their connections to the motor system. Thus, categorization is distributed over all these areas and cannot be separated out of the system. In this respect, the term "classification couple" used by Edelman to designate the reentrantly coupled feature maps is somewhat misleading.

Experiments

Learning performance

The behavior of the robot as it moves around in the environment and explores objects is shown in figure 9. The trajectories were recorded with a video camera and then hand traced. Figure 9 (left) shows a typical

trajectory at the beginning of a trial. White and shaded circles indicate non-conductive/non-textured and conductive/textured objects, respectively. It can be seen that there is no distinct behavior for the two types of objects. Rather the robot approaches all objects and explores them. Figure 9 (right) shows a typical trajectory after the robot has encountered 10 objects of each type. Two main results can be taken from the traces in figure 9.

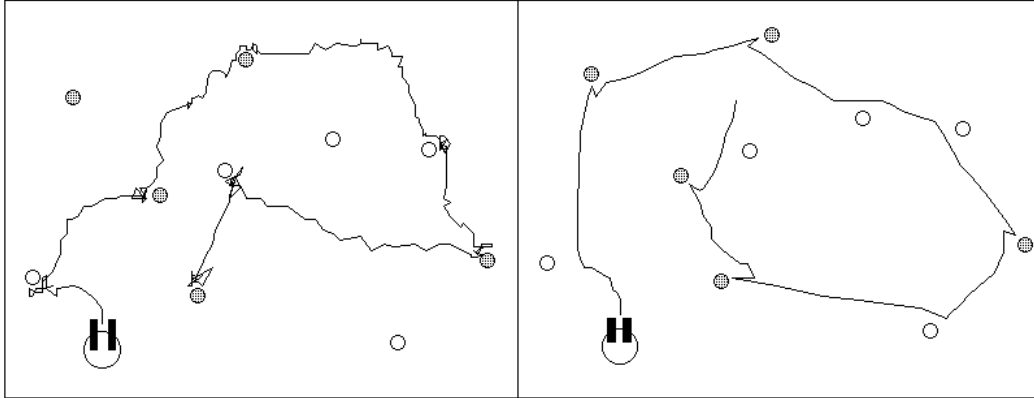


Figure 9: A typical trajectory of the robot initially (left) and after it had encountered 10 objects of each type (right).

First the robot has stopped exploring both types of objects because the behavior is now governed by the dynamics of the coupled feature maps. Second, the robot "ignores" non-conductive objects while it grasps conductive ones (without first exploring them). We use the term "ignoring" instead of "avoidance" to indicate that there is no separate avoidance module. Rather, the avoiding is achieved by not sustaining the activation in the attentional sensory-motor loop. In order to quantify this learning process the number of non-conductive objects explored and ignored was recorded for 20 trials. Each trial ended when the robot had encountered 40 non-conductive objects. Figure 10 shows the cumulative number of non-conductive objects the robot explored and ignored, averaged over all 20 trials.

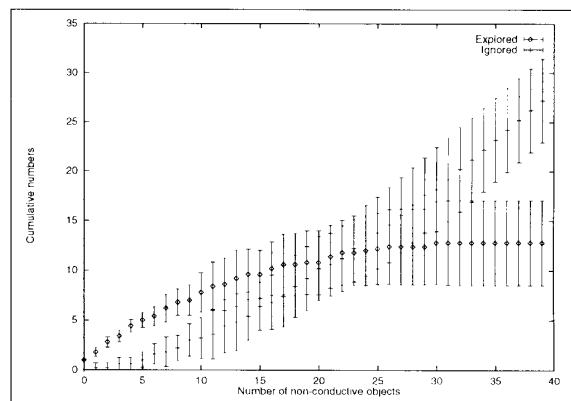


Figure 10: Cumulative number of exploration and ignore steps for 40 non-conductive objects encountered. The data are means (\pm sdev) over 20 trials.

At the beginning of the trials the agent always explored non-conductive objects. After it had explored around 6 objects it started to ignore them. Because the weights had not been sufficiently evolved it still explored some of the objects. After having encountered around 12 non-conductive objects the robot only explored because of errors in the sensory readings. A detailed analysis of the internal dynamics underlying this learning process can be found in Scheier and Lambrinos ([27]).

Discussion

We now relate SMC II back to the functions of sensory-motor coordination outlined in the introduction. For reasons of space we only discuss three of them. First, a foveation mechanism is used to focus the fovea on interesting regions in the environment. The sensory-motor coordination here is a reflex based on the fovea and the (simulated) "eye muscles". It leads to a significant decrease of the number of degrees of freedom in the visual space because only the foveated part of the image has to be considered. This illustrates the information-theoretic aspect of sensory-motor coordination (3). Second, so-called attentional sensory-motor loops are used. The visual attention loop causes the robot to orient and move towards objects while the haptic attentional loop results in focussing of the object: the robot moves its body in such a way that the object ends up in the front of the robot. As a result the robot can explore the object by lowering the arm over the object and closing its gripper. This allows the robot to gain physical control over the object (1). Finally, sensory-motor coordination was involved in the category learning itself. In essence, this learning is based on the crossmodal association between the haptic and the visual feature maps (4). It allows the integration of several sensory modalities.

SMC III: Garbage collecting in outdoor environments

The SMC III model is currently being implemented. Since our main interest is on sensory-motor coordination more complex sensors and actuators will be used. Currently, a 2-DOF active vision system mounted on a caterpillar robot has been built. With this system it becomes possible to investigate yet another important aspect of sensory-motor coordination, namely the dynamics and role of the oculomotor system for perception and categorization. This active vision system will be integrated with a 5-DOF arm in order to allow more complex experiments on sensory-motor coordination. The task of SMC III will be to collect garbage on the university campus, i.e. in a real world, outdoor environment. The main goal will be to test the concepts developed in the SMC I and SMC II models in a real world task.

Discussion

Experimental results

Let us go back to our definition of categorization and learning that we gave at the beginning. It was defined in purely behavioral terms. The behavioral data summarized in table 1 and in figures 9 and 10 show that with both the SMC I and the SMC II architectures, the agents learn to categorize the different types of objects. In SMC I the number of steps required before the agent "recognizes" the object, i.e. starts the appropriate interaction with the object, is significantly reduced from around 40 steps to a value between 11 and 15. In SMC II the robot successfully learns to ignore non-conductive objects while collecting the conductive ones. We have shown that this works because in both cases through the sensory-motor coordination, time-locked activation is generated.

Learning, development, and value

While performance is one point, there is a more important developmental issue. We are not primarily interested in performance, but in the nature of intelligence. This is why we want to study learning, in particular learning from the agent's own perspective.

One of the basic questions we always have to ask ourselves is what to define or design into the agent, and what the agent ought to acquire by itself. One extreme position is that everything—sensors, morphology, control—has to be evolved. The other extreme is that everything can be designed into the system. Intelligent behavior can be explained at various levels. It is typically the intermediate positions where we find the most powerful explanations. In the experiments described in this paper, we focus on learning and

development, starting with a given genetic set-up, letting the agent interact with the environment, trying to understand how its behavior develops over time.

We define the morphology, the sensors, the motor system, the learning mechanisms, and what we have called the value system. There is an implicit and an explicit aspect to the value system. The explicit one actually consists of mechanisms, typically neuronal ones, which are connected to the sensory-motor apparatus. An example would be that if a particular behavior can be executed, a reinforcement signal is automatically generated. For example, grasping is associated with intrinsic pleasure: the act of grasping is itself rewarding. It is therefore a good idea for the learning mechanism to reinforce the sensory-motor sequence before the successful event.

The implicit aspect of the value system is whatever is attributed by the observer to the behavior of an agent. In a sense, anything on the robot constitutes value. For example, we, as observers, say that it is good for an agent not to hit obstacles. Thus, avoiding obstacles is of value. It is also of value to be near objects, because being nearby bears the potential for physical control over the objects say, for eating or building a nest. Moreover, it is of value to the agent if it can grasp objects. As engineers, we have built our agents such that they display these behaviors. As described above, we have implemented a number of reflexes to increase the probability that something interesting, something of value to the agent, occurs. This speeds up value-based learning by orders of magnitude. But it is a general-purpose reinforcement scheme, and any interactions with the environment leading to success (i.e. value signals being generated) can be learned in principle. The reinforcement learning algorithm itself is part of the implicit value system. The algorithm is based on the assumption that it is good for the agent to maximize value over time.

In this perspective, the reflexes have a number of functions. First, they provide a certain amount of coarse adaptivity to a particular environment. Second, they tend to lead to sensory-motor coordinations which can be exploited by the agent. And third, they increase the probability of successful interactions with objects.

Exploration-based learning

So far, we have argued that having reflex behavior is of value to an agent. Similarly, we could argue that it is always of value to the agent to categorize its environment in some ways, whether there is a value signal directly associated with the categorization or not. This is roughly the approach taken in the second architecture with exploration-based learning.

We say that exploring objects is intrinsically rewarding itself and that during the process of exploration learning can already take place. The basic reflexes which lead to the exploratory behavior (as, for example, implemented by the “explore-object” process), are exactly the same as before.

This kind of learning has been implemented by the sensory-motor map discussed above using the DGCS algorithm. While in terms of resulting behavior there is not much difference, there is a lot of difference if we look at the internal mechanisms. Exploration-based learning occurs in the sensory-motor map. The algorithm is incremental, i.e. new objects can be added in at any time. Simply new nodes are being recruited. In other words, in complex environments (many different types of objects), more nodes are allocated. The topology also varies locally, but that cannot be illustrated here, since the whole space is, basically separable in one dimension.

However, the point that we want to make is a different one. Before, learning was tied directly to value signals being generated. In the exploration-based architecture, the value signals only influence that part of the learning process which associates the already formed categories of the sensory-motor map with the various processes (grasping, pushing, turning-away).

The DGCS-algorithm promises to scale up to learning in more complex environments. But conceptually, this approach with the sensory-motor map is very different. In a sense, we introduce a kind of

categorization *module*. It is a bit like moving the business of categorization, which was considered a property of the agent as a whole, into a particular internal component. This is somewhat reminiscent of information processing approaches of classical AI. We say “somewhat” since the whole procedure only works because of the sensory-motor coordination, and the latter only works because the neural net is embedded in a real-world autonomous agent. But still, there is this information processing module which—to some extent—“decouples” the categorization from the rest of the agent.

This fits, of course, well with our intuition of how we think humans work, and it is one of the reasons for the popularity of neural network algorithms based on maps: humans can learn, even if the learning is not directly associated with value.

But how do we know that this module delivers the right sort of categorization that matches the structure of the value system? The answer is, we don’t. The reason it works well in the experiments is because we chose the environment such that it fits in with the value system. The reason for this correspondence in natural systems is that typically evolution produces “ecologically balanced” designs. The hypothesis here is as follows: If the robot had evolved (which it has not, it was designed), evolution would have produced a map for categorization that is balanced with respect to the complexity of the value systems. If it were too sophisticated, what the agent learns, could never be really exploited. This can be derived from the principle of “ecologically balanced” designs introduced above.

In sum, in pure value-based learning, and in exploration-based learning, there is a coupling between category learning and the value system. In the former case, it is directly coupled by the mechanisms implemented in the agent. In the latter, it is coupled by the designer who complies with the principle of “ecologically balanced” designs. In evolutionary considerations the map should evolve to match the complexity of the value system. In this sense, evolutionary considerations can help us come up with good designs, even if the evolutionary process itself is not modeled explicitly. In a similar sense, the subsumption architecture is also based on evolutionary considerations (e.g. [5]).

Separating modules “out” is always a dangerous operation and has to be considered with great care. One of the basic questions is why the agent should categorize the world in the first place. We, together with many others, suggest that it is because it has to perform certain actions. Milner and Goodale ([20]) convincingly demonstrate that the primary function of the visual system in most species is motor control. In other words, categorization depends on the particular actions that need to be executed. Only if there is a motivation, the agent will learn about the various categories. Why, otherwise, should a distinction be made?

Grounding

One of our long-term goals is to understand what psychologists call concept formation. There is an increasing body of literature suggesting that concepts are firmly grounded in sensory-motor coordination, rather than being information processing constructs (e.g. [29]; [30]). In this paper we have tried to show in very concrete terms, how something like concepts might emerge. If we look at the behavior of the agent, it makes sense to attribute to the agent the following concepts: “graspable objects”, “pushable objects”, and “uninteresting objects”. We can now ask how these categories are represented internally. In the pure value-based case, the “representation” is given by the association strengths between the nodes in the input layer and the networks for the various processes. This connectivity matrix is the reason that for certain activation patterns of the sensory-motor space, certain process networks receive significant activation. In this sense, the categories of the agent are fully grounded. “Representation” is put in quotes because it is the observer that makes this correspondence between internal state and the outside world, not the agent itself.

The categories are only formed if the agent encounters objects with particular properties. Though there is the potential for forming more categories the agent will only form two if the environment contains only two types of objects.

In exploration-based learning, the “representation” of the categories is more obvious, more explicit. The categories are also grounded in the agent’s sensory-motor set-up, but they are less directly grounded in the value system.

We have not talked about “symbol grounding” because that would require symbols that need to be grounded. In our approach, there are no symbols, except in our own descriptions of the mechanisms as used in this paper. They are not part of the agent and need therefore not be grounded.

Scaling: getting away from predefined values

The reader might get the impression that most of what the agent learns is in fact somehow predefined, in particular that the categories are somehow given. This requires a bit of discussion.

It is true that we do predefine many things: we define the morphology, the sensors, the effectors, the value system, the learning algorithm, etc. But because we have a self-supervised learning mechanism, the actual behavior of the agent depends on its interaction with the environment, on its experience, on its history. While we have not modeled the development of morphological structures, we have modeled parts of the neural development (including structural changes of the network architecture). What we design is the *potential* for categorization, not the categories themselves. What we would need to do to make the case study more convincing would be to increase dramatically the complexity of the sensory-motor system and the neural substrate. While the sensory complexity is easily increased—we can simply use a high-resolution CCD camera—it is more difficult to increase the motor complexity. But the principle of “ecological balance” tells us that it is not sensible to merely increase the complexity of one component.

If the complete agent were more complex, it would become more obvious that in particular environments only a part of its behavioral potential is exploited. The unexploited part bears the potential for reacting in interesting and perhaps novel ways to changing environmental conditions. An example is that blind people exploit the potential of the auditory and the haptic systems to a much larger extent than people with normal vision. With the SMC III project for a garbage collecting robot we hope to make significant progress in this direction.

Related work

In addition to the work that we have already mentioned in neurobiology, developmental psychology, and cognitive psychology, there is important work on autonomous agent navigation and categorization by Gaussier and Zrehen ([12]). They are focussing more on the visual aspects than on sensory-motor coordination. Then there is the seminal book of Georg Lakoff ([17]) which has provided us with a lot of inspiration. We feel that the approach outlined in this paper is largely compatible with Lakoff’s views on categorization. Finally, there is a lot of work on categorization in the connectionist community (e.g. [28]). Much of the connectionist work deals with mapping inputs onto certain outputs, the categories. This is normally done by supervised methods. If the categories are not known a priori—a condition which is fulfilled for our agents in the real world—non-supervised schemes like Kohonen maps or reinforcement schemes are applied. Just as in the case of supervised methods, Kohonen nets are typically trained with patterns from a data set which is predefined by the designer of the algorithm. If the network is part of a mobile agent, there is continuously changing stimulation of the sensors which implies that there is no neat set of well-prepared patterns. The agent has to decide on its own what to react to, what is relevant to categorization, and what to learn. Note that this is a problem that will have to be resolved by any mobile real-world agent.

Conclusions

One of these truly hard problem concerns the issue of categorization. We showed that if the problem is viewed as one of sensory-motor coordination, rather than one of information processing only, i.e. as one of mapping a proximal stimulus onto an internal representation, matters may become much simpler.

We feel that it is time to replace the information processing metaphor in the study of intelligent systems by the one of sensory-motor coordination. We hope to have demonstrated the power of this metaphor. Let us conclude by saying that it is much more than a metaphor. It offers concrete mechanisms for putting agents to work in the real world.

The real question is, of course, whether the processes related to sensory-motor coordination will be sufficient to account for the so-called high-level functions of cognition like memory, planning, language, and abstract problem solving and reasoning. Will something else, for example a particular symbol processing module, be required? We do not a priori deny that — it is an empirical question. But it is our research strategy to introduce additional features and mechanisms only if there is an unequivocal need for them. Given the tasks that we have studied so far and given our next tasks, this need has not arisen -- and we do not foresee that it will in the near and intermediate term future.

References

- [1] Ahrns, I., Bruske, J. and Sommer, G. (1995). On-line learning with dynamic cell structures. In: *Proceedings of the International Conference on Artificial Neural Networks (ICANN 95)*, October 1995, 141-146.
- [2] Ballard, D. (1991). Animate vision. *Artificial Intelligence*, **48**, 57-86.
- [3] Barsalou, L.W. (1992). *Cognitive psychology: An overview for cognitive scientists*. Hillsdale NJ: Lawrence Erlbaum.
- [4] Bauer H.-U., and Pawlezick, K.R. (1995). Quantifying the neighborhood preservation of self-organizing feature maps. *IEEE Transactions on Neural Networks*, **3**, 570-578.
- [5] Brooks, R.A. (1991a). Intelligence without representation. *Artificial Intelligence*, **47**, 139-160.
- [6] Bushnell, E.W. and Boudreau, J.P. (1993). Motor development and the mind: The potential role of motor abilities as a determinant of aspects of perceptual development. *Child Development*, **64**, 1005-1021.
- [7] Dewey, J. (1896). The reflex arc concept in psychology. *Psych. Rev.*, **3**, 357-370. Reprinted in: J.J. McDermott (1981) (ed.). *The philosophy of John Dewey*. Chicago: University of Chicago Press.
- [8] Douglas, R.J., Martin, K.A.C. and Nelson, J.C. (1993). The neurobiology of primate vision. *Baillière's Clinical Neurology*, **2**(2), 191-225.
- [9] Edelman, G.E. (1987). *Neural Darwinism. The theory of neuronal group selection*. New York: Basic Books.
- [10] Edelman, G.M. (1989). *The remembered present*. New York: Basic Books.
- [11] Fritzke, B. (1995). Growing cell structures — a self-organizing network for unsupervised and supervised learning. *Neural Networks*, **7**, 1441-1460.
- [12] Gaussier, P. and Zrehen, S. (1995). PerAc: A neural architecture to control artificial animals. *Robotics and Autonomous Systems*, **16**, 291-320.
- [13] Gluck, M.A. and Bower, G.H. (1988). From conditioning to category learning: An adaptive network model. *Journal of Experimental Psychology: General*, **117**, 227-247.
- [14] Grossberg, S. (1987). Competitive learning: From interactive activation to adaptive resonance. *Cognitive Science*, **11**(1), 23-64.
- [15] Kruschke, J.K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Review*, **97**, 225-252.

- [16] Kuperstein, M. (1988). Neural network model for adaptive hand-eye coordination of single postures. *Science*, **239**, 1308-1311.
- [17] Lakoff, G. (1987). *Women, fire, and dangerous things. What categories reveal about the mind.* Chicago: The University of Chicago Press.
- [18] Lambrinos, D. and Scheier, C. (1995). Extended Braitenberg Architectures. *AILab Technical Report*, University of Zurich, No. 95-10.
- [19] Martinez, T. (1994). Topology representing networks. *Neural Networks*, **7**, 505-522
- [20] Milner, A.D., and Goodale, M.A. (1995). *The visual brain in action.* Oxford: Oxford University Press.
- [21] Palmer, C.F. (1989). The discriminating nature of infants' exploratory actions. *Developmental Psychology*, **25**, 885-893.
- [22] Pfeifer, R. (1993). Cheap designs: exploiting the dynamics of the system-environment interaction. Three case studies on navigation. In: Conference on "Prerational Intelligence — Phenomenology of Complexity Emerging in Systems of Agents Interacting Using Simple Rules." Center for Interdisciplinary Research, University of Bielefeld, 81-91.
- [23] Pfeifer, R. (1996). Design Principles for Autonomous Agents. In: *Proc. SAB96*.
- [24] Ruff, H. A. (1984). Infants' manipulative exploration of objects: Effects of age and object characteristics. *Developmental Psychology*, **20**, 9-20.
- [25] Scheier, C. (1996). Incremental category learning in a real world artifact using growing dynamical cell structures. In: *Proceeding of the European Symposium on Artificial Neural Networks (ESANN '96)*, 117-123.
- [26] Scheier, C. and Pfeifer, R. (1995). Classification as sensory-motor coordination. In: *Proc. ECAL-95*. 657-667.
- [27] Scheier, C. and Lambrinos, D. (1996). Categorization in a real-world agent using haptic exploration and active perception. In: *Proc. SAB96*.
- [28] Shanks, D. (1991). Categorization by a connectionist network. *Journal of Experimental Psychology: Language, Memory and Cognition*. **17**(3). 433-443.
- [29] Smith, L.B., and Thelen, E. (eds.) (1993). *A dynamic systems approach to development. Applications.* Cambridge, Mass.: MIT Press, Bradford Books.
- [30] Thelen, E. and Smith, L. (1994). *A dynamic systems approach to the development of cognition and action.* Cambridge, Mass.: MIT Press, Bradford Books.
- [31] Tistarelli, M. (1995). Active/space-variant object recognition. *Image and Vision Computing*, **13**, 215-226.

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