Representation in situated models of cognition

Individual Course
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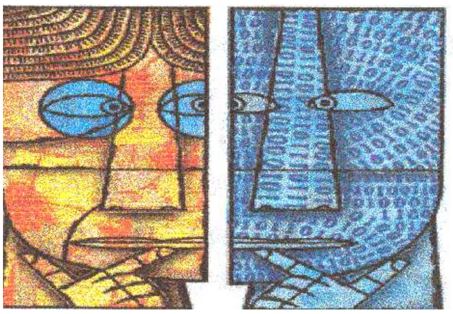

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Abstract

This paper discusses the nature and necessity of representation in explaining cognitive behavior. While representational theories dominated the history of Artificial Intelligence, a new approach, Embodied cognitive science,gained more popularity among cognitive scientists. Embodied cognitive science emphasizes a more anti-representational view. Where most debates concerning representations occurred on a philosophical level, embodied cognitive science gives existence to a new framework that allows concrete models and provides new methods of analysis. Further this paper discusses the strength of embodied and situated models in explaining biological behavior and psychological phenomena. By describing two concrete models we are showing that embodied and situated models of cognition provides new insights and is complementary to sciences as biology and psychology.

1 Introduction

Research in Artificial Intelligence (AI) is divided in two. On one side we have the traditional view, which states that cognition is nothing more than computations performed on representations. In this view, perception and motor interfaces are sets of symbols on which the central intelligence system operates (Brooks, 1990). This approach forms a tight analogy with computer programs, with algorithms (computations) operating on data structures (representations) (Thagard, 1996). Another view is that of embodied cognitive science which give more importance to the interaction between body and environment. This view is based on two fundamental characteristics, embodiment and situatedness. A system should be embodied so it can sense its environment true its sensors and act upon it through its actuators. The system should be situated in order to interact with its environment (Pfeifer and Scheier, 1999; Kortmann, 2001; Dawson, 2002). This approach contrasts the view of traditional cognitive science, that cognition is regarded as an abstract process that can be studied without taking the physical aspects of natural systems into account (Nolfi, 2002).The aim of embodied cognitive science is to understand how high-level cognitive processes, like reasoning and language, arise from low-level interactions with the environment.

The focus of this paper is the contrast between the traditional approach and embodied cognitive science concerning representations. While the first states that behavior and intelligence is based on representations, the latter rejects the use of representations in cognitive behavior. Eventually a new notation, that of "internal states", is proposed. The main difference between both, is that internal states are not explicit and complete models of the world(in contrast to the symbolic representations used by the traditional approach).

Section 4 shows how models in embodied cognitive science can be used to test hypotheses of specific biological behavior. Further two specific models are described to give an example of how situated models can model biological behavior and explain psychological phenomena. Section 4.1 gives a sensory-motor account to vision and section 4.2 describes how we can model psychological phenomena in developmental psychology using situated models.

2 Artificial Intelligence in a historical perspective

2.1 Traditional AI and Cognitive science

The question whether it was possible for a computer to think, came with the rise of computer technology in the early 1950's. With the progression that was made by computer technology came a progression in the development of formal logic and computational theory. Artificial intelligence (A.I.) was founded in 1956 by researchers as John McCarthy, Marvin Minsky, Allan Newel and Herbert Simon. Their attempts were to replicate human level intelligence in a machine (Brooks, 1991a). These researchers where interested in the great power of abstract symbol systems that undergo rule governed transformation. In the 1930's, before the rise of the computer technology, Alan Turing stated on pure mathematical grounds, it was possible to construct an electronic machine with conscious intelligence. He believed that the physical properties of a system were completely irrelevant. This 'Universal Turing Machine' could compute every possible mathematical function. The challenge for A.I. was to find the right input/output function to model the mind. Early work in A.I. concentrated on games, geometrical problems, symbolic algebra, theorem proving, and other formal systems (Brooks, 1991b; Brooks, 1990).

At the same time, researchers in several other fields began to develop theories of the mind based on complex representations and computational procedures, which would eventually lead to a new research paradigm, cognitive science. Cognitive science is the interdisciplinary study of the mind and intelligence (Thagard, 1996). It started in the 1960's when psychologists, philosophers, neuroscientists, linguists and computer scientists joined forces in order to understand complex mental tasks such as thinking, language, problem solving...etc (Gardner in Kortmann, 2001). The use of (symbolic) representation plays a central role in the cognitive science approach. Cognitivists agree that knowledge in the mind consists of mental (symbolic) representations. Thought and action are a result of certain procedures that act on these representations (Thagard, 1996). In this view, the human mind is regarded as a very powerful computer which receives input from the world through its sensors. This input forms an internal model (representation) of the world. Depending on the state of the system, certain computation are performed on these representations, which result in a specific behavior or output (Pfeifer and Scheier, 1999).

2.2 A new approach - Embodied Cognitive Science

As a result of some disadvantages and shortcomings (which will be treated in the following sections) of the traditional approach to understand intelligent behavior, a number of researchers, somewhat independently, began rethinking the general problem of organizing intelligence (Brooks, 1991a). This new approach, embodied cognitive science, emphasizes that intelligence should be studied as an interaction between body and environment, where the dynamics of the environment directly influences the behavior of the system. Furthermore, embodied cognitive science argues that theories of intelligence should exhibit two basic characteristics (Dawson, 2002). First, embodiment, meaning that in order to study intelligence we need a system with a physical body that interacts with an environment. The idea that intelligence can emerge only from embodied agents is one of the fundamental assumption of embodied cognitive science (Brooks, 1991b). Second, the embodied system should be situated in an environment, which means that an embodied system (robot or simulation) must be able to interact with an environment. An agent is situated if it can acquire information about the current situation through its sensors in interaction with the environment (Pfeifer and Scheier, 1999). This means that situated agents are dealing with the 'here' and the 'now' of an environment which not only enables them to perceive the state of the dynamical environment at every time, but also enables them to actively manipulate their environment. This brings us to another principle of fundamental importance in embodied cognitive science, sensory-motor coordination, which will be further discussed in 3.2.2 (Pfeifer and Scheier, 1999).

3 Representations

3.1 Representations in the traditional, cognitivist view

The cognitivist view emphasizes a computational-representational approach in order to understand human intelligence. The central hypothesis in the cognitivist view is therefor CRUM, Computational and Representational Understanding of the Mind (Thagard, 1996). Although there is much disagreement about the nature of representation, it is known that traditional cognitive science uses a more explicit form of representation.

For instance, the robot Shakey, developed at the Stanford Research Institute, was built to navigate itself in a set of specially prepared rooms (Brooks, 1991a). It was equipped with a camera and a symbolic planning system called STRIPS. Shakey's task was to navigate autonomously from one room to another, to avoid obstacles, and to push boxes from room to room (Pfeifer and Scheier, 1999). The planning program STRIPS, operated on a symbolic description of the world to generate a sequence of actions. While Shakey did its job well in a strictly predefined environment, it could not function in an environment for which it was not designed. Furthermore, Shakey was sensitive to noise and could not operate in a dynamic environment. This brings us to two important theoretical issues concerning the use of symbolic representation of the world.

One is the frame problem, which was originally pointed out by McCarthy and Hayes (1969). It refers to the difficulties with representing, or model, change (Kortmann, 2001). If an intelligent system uses symbols to represent its environment, how can it be kept in tune in a continuously changing environment? Suppose you want to represent a green box using a symbol system. When you move the box, it turns a bit, the light intensity changes, ... etc. But what happens with the symbol you use to represent it? It is even worse in a dynamical environment where a lot of things need to be represented simultaneously by the symbol system. It is hardly possible that an intelligent system could efficiently use symbolic representations of the world for all their behavioral patterns (Brooks, 1991b). The environment in which Shakey had to operate was very simple , the walls were of a uniform color and carefully lighted, with dark rubber baseboards making clear boundaries with the lighter floor. The rooms were bare, except for the large colored blocks and wedges, so it was simple to represent the the objects in the environment (Brooks, 1991a).

Second, these symbol systems have to deal with the symbol grounding problem, which refers to how symbols relate to the real world (Harnad, 1990; Searle, 1990; Pfeifer and Scheier, 1999). The question is, how can the meanings of these meaningless symbols, that are being manipulated on base of their shapes rather than meanings, be grounded in something else than other meaningless symbols? Around 1980, John Searle presented the Chinese room thought experiment as an argument against the claims of these symbols systems (Searle, 1990) This thought experiment eventually led to the symbol grounding problem.

These problems are less significant in highly abstract domains like chess or problem-solving tasks with finite states, in which a system does not need to know what the relation is between its symbols and the real world(Kortmann, 2001). But if we want to understand intelligence in a more natural dynamical environment we need a different approach which emphasizes the relationship between the body and the environment, and overcomes the problems with which the traditional approach is faced. Within the traditional AI approach, there is a tendency to view internal representations as explicit and complete representations of the external world (Nolfi, 2002). The use of these formal systems in traditional AI underestimates the importance of the behavioral context.

3.1.1 Tri-level hypotheses

In order to understand cognition in terms of computation and representation, Marr proposed his tri-level hypothesis. Marr stated that there was need for

> Additional levels of understanding at which the character of the information processing task carried out ... are analyzed and understood in a way that is independent of the particular mechanisms and structures that implement them in our heads. (Marr in Clark (1997), p84)

In his tri-level hypothesis, Marr proposed to divide the explanatory task in three different levels of analysis. First the computational level, which is a general analysis of the task being performed. The computational level is a description of the input-output function of a particular system and addressing the question which subtasks are needed to solve this problem (Clark, 1997). The second level of analysis is the algorithmic level, which focuses on the specific steps or subtasks that are needed to solve the task. This level is concerned with how the input and output is represented and how the input is transformed (computed) into the output (Marr, 1982). Finally, the implementational level, which outlines the physical properties and implementations of such a system. Much work in traditional cognitive science is concentrated at the first two levels and causing models to neglect the importance of the understanding of the brain and body. The brain was seen as a physical device that merely implemented computational and information-processing strategies, and is therefor mindless (Clark, 1997).

A major drawback in traditional cognitive models is that they often minimize (or ignore) the importance of the body and its interaction with the environment, sice most models and theories are concentrated on the computational and algorithmic level of analysis.

3.1.2 Marr's computational approach to visual perception

Most (current) theories about vision and perception still rest on the idea that our brain produces some sort of internal representation of the world which gives us the experience of seeing the world. A major contribution in understanding the principle of visual perception came from Marr. His theories had an enormous influence on pattern recognition in traditional cognitive science. According to Marr, visual processing involves three steps. First, raw sensory information of the visual image is deduced and specific information from the image is made explicit (Gordon, 1989). The most important information in this step involves identifying object edges, contours, ... etc and the manner in which they are organized (Matlin, 1994). This leads to an abstract representations that Marr called the primal sketch (Gordon, 1989; Matlin, 1994). The next stage is the $2\frac{1}{2}$-D sketch that is a transformation of the primal sketch, in which information about orientation and depth are made explicit (Gordon, 1989). Finally, the 3-D sketch, which is a more accurate representation of the world. The main difference between the $2\frac{1}{2}$-D sketch and the 3-D sketch is the independent of the viewpoint of the observer. The $2\frac{1}{2}$-D sketch is representing only from the viewpoint of the observer whereas the 3-D sketch is independent from the observer viewpoint.

3.2 Representations in embodied cognitive science

In order to understand the view of embodied cognitive science on representation, I start with a metaphor by Simon (Simon in Pfeifer and Scheier (1999)) to illustrate some basic principles of behavior.

Simon imagined an ant walking along the beach, and that its trajectory along the beach was traced. From the observer's point of view this ant makes a complex trajectory on the beach between rocks, puddles,...etc. The observer might be tempted to address this complex behavior to fairly complicated internal navigational processes (Dawson, 2002). Maybe the ant has an internal model of the environment, with goal states...etc. Such an explanation would lead to an incorrect theory, because it would be a mistake to assume that the entire path or the environment is stored in the memory of the ant. From the perspective of the ant, the world looks completely different because of its entirely different embodiment (different sensors, different brain, different body) (Pfeifer and Scheier, 1999). The complex path of the ant can better be explained as a result of local interaction with the environment. the complexity of the path is actually a complexity in the surface of the beach and not a complexity in the ant (Dawson, 2002). These local and simple interactions between body (with its sensors and actors) and the environment, such as following the scent of a pheromone trail, object avoidance, could lead to a complex trajectory. The behavior of the ant looks very complicated to an observer, but it came about by applying simple rules.

The point is that the complexity of the ant its trajectory emerges from an interaction of the ant with its environment and not from internal mechanism alone (Pfeifer and Scheier, 1999). Embodied cognitive science gives more importance to the interaction between agent and the environment. This approach differs enormously from the traditional approach in which the complexity of behavior is situated in the mind and were the physical properties of a system are regarded completely irrelevant.

Given this importance of interaction with an environment we cannot longer define representations as explicit and complete models of the world, like in traditional AI. Embodied cognitive science emphasizes a completely different view about the existence, or use, of representations in intelligence. Before rethinking the problem of representation, with respect to embodied cognitive science, we first need to emphasize an other concept in embodied cognitive science, sensory-motor coordination. Before explainig sensory-motor coordination we first look at Gibson's direct perception theory, who's theory was the basis for sensory-motor coordination.

3.2.1 Gibson direct perception theory

Gibons direct perception theory contrasts Marr's approach about visual perception. Marr claims that perception is indirect and that the sensory stimulus is not enough to produce the perceptual response. Something needs to be added, the incoming stimuli must first be elaborated into images, schemata or models (Gordon, 1989). This implies that we do not perceive the world as it is, but that we experience representations constructed from information of the world. However Gibson , claims that visual perception is direct, and that no representations, higher order processes, or anything, is needed to perceive the world. Gibson was the first to stress the importance of movement in perception. 'Perceiving is an act, not a response, an act of attention, not an triggered impression, an achievement not a reflex' (Gibson in Gordan 1996; p146). Perception is active and exploratory rather than passive, and changes that result from our motor behavior should therefor be a part of the process of perceiving. The importance of action in perception is one of the core assumptions of sensory-motor coordination.

The concept of the *invariant* is of fundamental importance in the direct perception theory. Invariance is a mathematical property, which refers to detecting constancies or correlations in changing visual scenes. For example, when moving toward an object one experience, a radial expansion of texture around one's head while the object we are moving towards stays constant. This change in the visual scene is not random, it follows a pattern of flow (Gibson, 1979; Gordon, 1989). Underlying this pattern of change is an invariant. There are several kinds of invariants that can provide information about our relation to the visual scene. According to Gibson,invariants are provided by the environment.

3.2.2 Sensory-Motor coordination

According embodied cognitive science, intelligence can be best understood within the context of the bio mechanics of the body, the structure of the environment and the continuous feedback between the nervous system, the body and the environment (Chiel and Beer, 1997). One cannot simply 'peel away' the body in order to understand the nervous system's role in intelligence. This continuous interaction between body and environment is captured in the concept of sensory-motor coordination which is of fundamental importance in embodied cognitive science. The underlying idea behind sensory-motor coordination can be best illustrated by a quote from John Dewey (Pfeifer and Scheier, 1999).

> We begin not with a sensory stimulus, but with a sensory-motor co-ordination.... In a certain sense it is the movement which is primary, and the sensation which is secondary, the movement of the body, head, and eye muscles determine the quality of what is experienced.

Dewey claims that perception and action are tightly coupled, and he calls this coupling "sensory-motor coordination" (Pfeifer and Scheier, 1999). This does not imply that sensory-motor coordination is a synonym for behavior. The behavior must be directly guided by the sensory input, an agent turning around its own axis is not engaged in sensory-motor coordination. The problem here is that the agent does not interact with the environment, and the control of its action is entirely within the agent itself (Pfeifer and Scheier, 1999). This would be sensory-motor coordination if the behavior of the agent was a result of the sensory input that altered the action of the agent.

3.3 To represent or not to represent

Cognitivists explain the mind in terms of internal representations and computations that work on them. From the above it is clear that embodied cognitive science approaches behavior and intelligence in a different manner, and therefor the notation of internal representations can no longer hold. Most researchers in embodied cognitive science completely reject the idea of internal representations. Clark describes this as the thesis of radical embodied cognition, which states that

> Structured, symbolic, representational, and computational views of cognition are mistaken. Embodied cognition is best studied by means of non-computational an non-representational ideas and explanatory schemes involving, e.g., the tools of dynamical system theory (Clark, 1996, p.148).

In the light of this thesis, refering to a intelligent system's inner processes as internal representaions is no longer feasible. Therefor they are preferably refered to as internal states (Beer, 1996; Chiel and Beer, 1997; Clark, 1997) According to Beer (Beer in Clark,1996) all kind of systems, for example nuclear power plants, can have complex internal states. But no one is tempted to treat them as some sort of representational devices. Therefor the only kind of internal states of any interest are, those that represent the environment in some way and which go beyond a mere correlation. For instance, there is a nice correlation between the tides and the position of the moon, but neither represents the other, since we do not find it plausible that the tides were selected for the purpose of carrying information about the position of the moon.

These internal states can be seen as a set of internal variables that are set as a result of environmental input, and cause the system to produce a certain output that fits the environmental conditions (Van Dartel, 2000). Clark states that 'The status of an internal state as representation depends not so much on its detailed nature (e.g., whether it's like a word, am image, or something entirely different) as on the role it plays within the system ... What counts is that it is supposed to carry a certain type of information and that its role, relative to the inner systems and relative to the production of behavior, is precisely to bear such information.'(Clark, 1997, p 146) It is important that the system uses the correlation, between environmental input and corresponding action as an output, in a way that suggests that the system of internal states has the function of carrying specific types of information (Clark, 1997). To some, this definition of internal states will sound similar to that of internal representations. However, internal states differ from representations in that they are not explicit and complete models of the external environment and secondly in that they do not undergo explicit rule governed manipulation. An advantage of defining the behavior mediating internal processes as internal states is that it creates opportunity, for embodied cognitive science, to discuss these processes without the bias implied by the term 'internal representations', suggesting complete explicit representations of the external world and rules that work on them.

Although the use of internal states makes it possible to describe a model in terms of representing its environment in some way, it is not exactly clear whether an agents has internal statesor not. According to Clark, even simple agents with sensory-motor couplings in the form of causal correlation between sensory states and behavior, have internal states. However Nolfi, makes a distinction between pure reactive systems, in which a system reacts to a sensory state by always producing the same motor action and non-reactive agents which may react to the same sensory state in different manners (Nolfi, 2002). According to Nolfi, internal states, if any, play a comparatively limited role in determine the motor output of pure reactive agents. Whereas, non-reactive systems need internal states in order to react differently when presented the same sensory states and a different reaction is required (Nolfi, 2002; Van Dartel and Postma, 2003). In this case the internal states can mediate how to react. In order to react differently to the same sensory inputs, an agent behavior must not depend only on its current environmental state, but also on its 'recent history of interaction with its environment' (Beer, 1996). The distinction between reactive and non-reactive agents can therefor be reduced to having (non-reactive) or not having (reactive) the ability to retain history information.

In the following two sections the difference between reactive en non-reactive agents will be discussed.

3.3.1 Reactive systems

Research in embodied cognitive science mostly involves agents that are reactive. The main reason for this is that reactive agents can solve rather complex tasks without internal states (Nolfi, 2002; Van Dartel and Postma, 2003).

In order to illustrate the concept of reactivity, its worth to take a look at a few thought experiments from neuroscientist Valentino Braitenberg (1984). In these thought experiments he presents a series of 14 agents, "Braitenberg vehicles" of increasing complexity. Lets take a glimpse at the first two Braitenbeg vehicles (Figure 1). Vehicle 1 is equipped with one sensor and one motor. The connection between sensor and motor is a very simple one, the more the sensor is exited, the faster the motor goes. Suppose that the sensor is sensitive to temperature (absolute temperature in degrees Kelvin) and that the force exerted by the motor is exactly proportional to the absolute

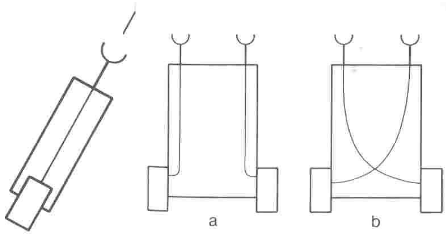

Figure 1:
On the right vehicle 1 with one motor and one sensor. Left side, vehicle 2a/2b, both with two sensors and motors. (from : (Braitenberg, 1984))

temperature (Braitenberg, 1984). The vehicle keeps moving in the same direction because the temperature is nowhere under 0 degrees Kelvin. The vehicle slows down in cold regions and speeds up in warm regions . One could say, as an external observer, that this creature likes cold places. Vehicle 2 is equipped with two sensors and two motors. Vehicle 2a has parallel excitatory connections and vehicle 2b has crossed excitatory connections. Lets assume sensors are light sensitive. Vehicle 2a will turn away from a light source because the sensor closer to the stimulus will get more excited and thus the motor closer to the source will turn faster, whereas vehicle 2b will turn towards the light source because of the crossed connections. The behavior of the two Braitenberg vehicles described here, are based on direct sensory-motor couplings with no internal processing. When we add more sensors (chemical, proximity, etc) and more(different kinds) of connections, or even a brain (neural nets), a single agent could be capable of performing survival enhancing behavior like finding nutrients, obstacle avoiding, learning, etc. These systems are all reactive insofar as their behavior is driven by direct reactions to environmental states.

Reactive agents are capable of solving rather complex tasks Nolfi (2002) showed that reactive agents, by exploiting sensory-motor coordination, can cope with perceptual aliasing. Perceptual aliasing refers to a situation where the same perceived sensory patterns require different responses. At first sight this problem can only be solved by a non-reactive system, because such a system can use its recent history of interaction with its environmental input, and can react differently to the same sensory state. However Nolfi showed that reactive agents can cope with this as well, because they are able, by means of sensory-motor coordination, to partially determine future sensory patterns received from the environment by changing their position (Nolfi, 2002). An agent can, when presented with an ambiguous sensory pattern, execute actions that lead to the perception of sensory patterns that are not ambiguous and thus not affected by the aliasing problem. In another experiment Nolfi (2002) showed, that reactive agents are able to cope with

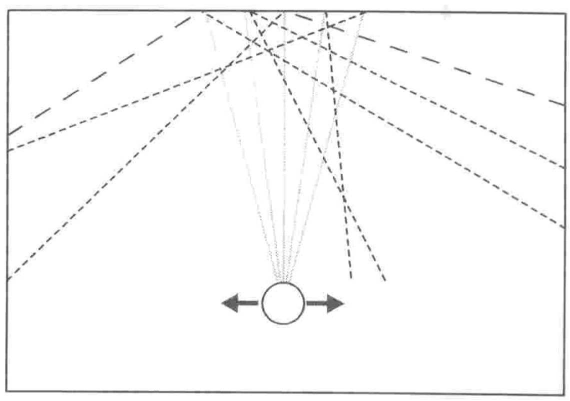

Figure 2:
Experimental setup for orientation experiment. The agent moves horizontally. Dotted and dashed lines denote the paths of circular objects. (from: (Beer, 1996))

the aliasing probleem even when all sensory states are ambigious. Agents solve this task by using the environment as an external memory (O'Regan and Noe, 2001; Van Dartel and Postma, 2003).

3.3.2 Non-reactive systems

Non-reactive agents do not react on basis of environmental states, like reactive agents, but also rely on their recent history of interaction with the environment. Unlike reactive agents, these systems make use of internal states to guide their behavior. One way of integrating and storing sensory information over time, is by using recurrent neural networks (RNN). These are neural networks that are provided with recurrent connections that project the output back to the input.

By means of an orientation experiment Beer (1996) pointed out some differences between reactive and non-reactive agents (Figure 2). He evolved agents with feedforward neural networks (reactive) and agents with RNN (non-reactive), that used their vision to adjust their horizontal position in order to catch falling objects

In the first set of orientation experiments the feedfoward agents were evolved and had a mean fitness of 90.25% over 100 random trails. This is a fairly good result, but the agents still missed some objects because the objects moved to quickly out of the visually field of the agents. They were not able to pursue objects that they could no longer see, because of their reactivity. Reactive agents cannot coordinate their behavior according to sensory stimuli that are no longer present (Beer, 1996). In the second set of orientation experiments Beer evolved agents controlled by RNN, in order to see if these agents could deal with this simple object persistence problem. The experimental conditions were the same as in the first set of the experiment. The mean fitness of the agents on 100 random trials was 96.60%. Although the difference in mean fitness on the 100 random trials between reactive an non-reactive agents is not large, this does not mean that this difference is not important. Examination of the behavior showed that the non-reactive agents were able to pursue objects even when they disappeared out of the visual field of the agentt. In this experiment, Beer showed that 'internal dynamics can offer significant advantages to an agent by allowing its behavior to depend not only on its immediate circumstances, but also on its recent history of interaction of the environment' (Beer, 1996).

4 Situated models and biological behavior

The strength of embodied and situated models of cognition is that they are useful to test hypotheses about mechanism of behavior, whenever this behavior is seen as a result of continuous interaction between body and environment. According to Webb (2000), building embodied and situated models involves the same steps as one would expect in building any model. First, a hypothesis needs to be explained, which gives rise to building a model to offer an explanation. Next, showing that the results account for the observed behavior. And, finally, make further predictions and testing them. Constructing embodied and situated models requires the solution of a large range of problems

> the researcher is forced to confront assumptions about the nature of the stimulus and the possible actions given real characteristics of the environment ... building systems in the real world often shows one's prior assumptions about the requirement to be completely wrong (Webb, 2000 p. 549).

This means that, in order to develop embodied and situated models, one has to carefully design an agent's body in respect to its environment (Pfeifer and Scheier, 1999). A body plan needs to be created in which actuator and sensor devices, the internal dynamics, the ecological niche ... etc are determined in resemblance to the biological equivalent. This way of modelling of behavior makes it possible to effectively characterize the problems the animal is faced with or needs to solve. Modeling in embodied cognitive science often involves an incremental or synthetic approach in which models progressively include more biological detail (Pfeifer and Scheier, 1999; Webb, 2000; Braitenberg, 1984). An example of a situated model of biological behavior that is often cited in neuroethology is cricket phonotaxis.In order to locate mates, female crickets use the phonotaxis mechanism to determining the direction of male calling songs. Building a model of cricket phonotaxis showed that much is known about the auditory systems and the identified neurons, but less is understood about connectivity and behavioral control (Webb, 2000). The first model of cricket phonotaxis was relatively crude but was able to show that a single mechanism can take account for both the approach behavior and the selectivity to song patterns (Webb, 2000). Although this model was a strong simplification of the problem, it still provided new insights that could be different from a priori assumption about the behavior. In the following models more biological detail was implemented. The third model was provided with spiking neurons (to carry out a more direct exploration of the function of timing in neural interactions), and was complex enough to allow behavioral and physiological tests on the model (Webb, 2001). One result of this research is that a 'recognition neural response' [1] ,that to biological studies showed to be critical, played no direct role in explaining the behavior.

The main criticism against these models is that they involve simplifications of the body, environment and internal dynamics. It is true that most models are tested in simplified environments and that the body is just an approximation of the 'real thing'. Nevertheless, these models show interesting resemblance to natural behavior, in a manner 'appropriate to test the hypotheses in question' (Webb, 2001). This abstraction can also be found back in traditional cognitive, biological and psychological models, in which experiments often involve controlled and simplified environments. An abstraction, for instance using a two-wheeled robot instead of a four-legged, doesn't always need to lead to a loss in biological relevance, as long as the abstraction is clear and justified and involves an approximation of the biological equivalence.

Situated models of cognition can give new insight in the understanding of biological behavior and cognition, and makes it possible to rethink (old)theories of behavior and cognition and view them from a different point of view.

4.1 Sensory-motor coordination and vision

The direct perception theory of Gibson has had a great influence on thinking about perception in psychology and AI. Similar ideas are found in O'Regan and Noe (2001). Central to O'regan and Noë 's approach is that 'vision is a mode of exploration of the world that is mediated by knowledge of what we call *sensorimotor contingencies*' (O'Regan and Noe (2001); p940). The sensorimotor contingencies are best understood by using a metaphor by O'regan and NoëImagine that you want to explore the remains of the titanic

[1] firing rates of a brain neuron that correlated with performance to a varying stimulus

with a remote-controlled underwater vessel. Due to some problems, the control cable is damaged and the connections to sensors, actuator, underwater camera's and sonars are mixed up. What appears on the screens, lights and beeps, in the control room is no longer making sense and the actuators no longer have their normal functions. The only thing that the engineers can do is observe the structure of changes that occur when they press several buttons. From this they could be able to deduce which buttons controls movement and which light correspond to information from the sensors. The brain is faced with the same problem. If it was possible to get inside one's eye, among the rods and cones, the only information available would be activations coming from them and not a part of an image (Gordon, 1989). Movement of the eye leads to a change in activation from the rods and cones. This continuously changing pattern looks very complex and chaotic, but is in fact non-random. Underlying this so called chaotic patterns is a 'structure of rules governing the sensory changes produced by various motor actions' which are called sensorimotor contingencies (O'Regan and Noe, 2001). These sensorimotor contingencies do not only refer to visual perception, but also to other sensory domains as audition, smell, touch, ...etc. Every different sensory modality obeys their own set of structure of rules. The similarities between Gibson's invariants and the sensorimotor contingencies are clear, both explain perception in terms of finding rules, constants and correlations in changing perceptual patterns. Still there is one fundamental difference between both views. Gibson claims that the invariants are provided by the environment itself, whereas O'regan and Noë believe that the invariants lie in the retinal stimulation and the knowledge of a system about these contingencies (Pfeifer and Scheier, 1999; Scholl and Simons, 2001).

4.1.1 internal states and vision

In Gibson's direct perception theory, the invariant information underlying perception was presented externally, and therefor makes no use of memory and representations. The world is a model on its own, and environmental cues just need to be picked up. Main criticism against Gibson theory was that, although he was successful in proposing a framework for perception without representation, it is still vague how these invariant are being detected (Gordon, 1989). These invariants are not explicitly presented in the environment, and therefor an internal process is needed to derive the invariants. Gibson never fully succeeded in developing a non-representational theory of visual perception.

According to the sensory-motor theory of vision, visual perception 'can be understood as the activity of exploring the environment in ways mediated by knowledge of the relevant sensory-motor contingencies' (O'Regan and Noe, 2001; p943). According to Scholl and Simons (2001) the term "knowledge", of the sensory-motor contingencies, is not that different from an internal memory or representation. The only difference from traditional object representation is that the knowledge in the sensory-motor theory is dynamic rather than static. What O'Regan and Noe (2001) mean, is that a system encounters a lot of visual attributes and visual stimuli over time with their own particular set of sensory-motor contingencies. Knowledge refers to a record of previous interaction with the environment that "remembers" the rules underlying each particular contingency. The term knowledge does not refer to an internal representation in the form of a set of rules that mediate the sensory-motor contingencies, but can best be understood as the internal dynamics of a system that has the ability to remember its previous interactions with the environment.

4.2 Modeling a baby : situated models in developmental psychology

Developmental psychology concerns the different stages of human development (cognitive, social, neuropsychological,..etc) from birth until death. Embodied cognitive science attention is given to the cognitive development of babies and concerns the fundaments of cognition and the role, or needs, of representations in the early stages of cognition.

In developmental psychology, computational models are gaining interest and researchers are recognizing the value of these models in the investigations of cognitive development in young infants (Schlesinger, 2002). Although these models provide new theoretical perspectives concerning the development of architectures, algorithms, ...etc, in order to explain early cognition, they still overlook a few very important principles of embodied cognitive science : an embodied and situated system that interacts with its environment (Pfeifer and Scheier, 1999; Zlatev and Balkenius, 2001; Schlesinger, 2002). According to Schlesinger (2002), modelling an *epigenetic*[2] (Zlatev and Balkenius, 2001) process requires an embodied and situated system, that is able to perceive the world through its sensors and can change its environment with its effectors. In the emerging field of Epigenetic Robotics psychology and robotics meet. Both disciplines have identified a number of common goals and benefit from each others research and knowledge. While psychology provides empirical findings and theoretical generalization, robotics implements these psychological theories, providing a variety of new insights in cognitive development (Schlesinger, 2002). This implementation in embodied and situated systems can "clarify, evaluate, and even develop psychological theories, which, due to the complexity of the internal processes involved, have hitherto remained somewhat speculative" (Zlatev and Balkenius, 2001; p1).

[2]The term epigenesis was introduced in psychology by Jean Piaget. It refers to development, determined by the interaction between the organism and the environment

4.2.1 A sensory-motor model of infant causal perception

In developmental research, two theoretical views are being proposed to explain infant's reaction to causal events. The first, top-down, view of infants causal knowledge, states that "infants use naive or intuitive physical principles to predict, reason about, or deduces the outcomes of causal events"(Schlesinger and Barto, 1999; p625). Computational models, supporting such a top-down view, help to illustrate the representations underlying the prediction of causal events. The second view advocates a bottom-up view of infant causal perception in which no representation is needed and more attention is given to associative learning and simple perceptual cues in the perception of causality (Schlesinger, 2002).

Instead of modeling causal perception of infants as a representational task, Schlesinger and Barto (1999) use an Optimal Control Model (OCM) to give a sensory-motor account of causal perception. OCM has no a priori knowledge, cannot generate predictions and learns by trial and error. OCM is reactive since it is controlled by a feedforward multilayer neural network. It learns a sequence of eye movements that maintains an object in view by rewarding eye movements that keep the target object within the visual field. During training OCM is presented with two causal events. First OCM was trained to track an object that passed behind a screen and reappeared on the other side. In the second event the object encountered a wall and then remained in place. After training the weights of the neural network are frozen and OCM tracking behavior was tested during a novel situation that involved both the wall and the screen. The analysis is concentrated on OCM's tracking behavior, in particular whether or not OCM moves its visual field to the right edge of the screen before or after the block reappears (Schlesinger and Barto, 1999). The *tracking latency* is defined as the difference in time between the first fixation of the right edge of the screen, and the block reappearance at the right. In the wall-screen trails the tracking latency is used, although the block will not reappear, by assuming the reappearance of the block would it not been obstructed. A positive latency means that the visual field fixates on the right edge of the wall after the block reappeared, a negative latency means that OCM anticipates on the reappearance of the block on the right edge of the screen (Schlesinger and Barto, 1999).

In a first(Figure 3) experiment OCM anticipates (negative latency) the reappearance of the occluded object during screen tests but not during wall-screen test (Schlesinger and Barto, 1999). OCM act as if it knows when the occluded path of the moving object is obstructed or not. It uses the presence of the wall as a cue for tracking the occluded object and therefore associates the sight of the wall with its effect on the object. Another explanation is that OCM learns nothing about the wall during the wall trails. It just learns to keep the visual field in place when the block stops moving. According

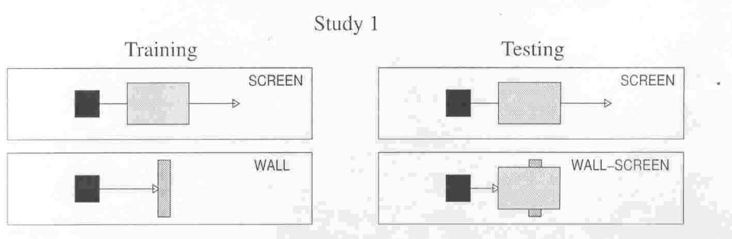

Figure 3:
Training and test events presented to OCM in study 1. (from : (Schlesinger and Barto, 1999))

to this explanation the presence of the partially occluded wall only disrupts the tracking behavior of OCM. Schlesinger and Barto (1999) conducted a second experiment to show that OCM uses the partially occluded wall as a cue. In this experiment the wall is placed back, from OCM's point of view, and the object is not being obstructed by the wall anymore (Figure 4). Re-

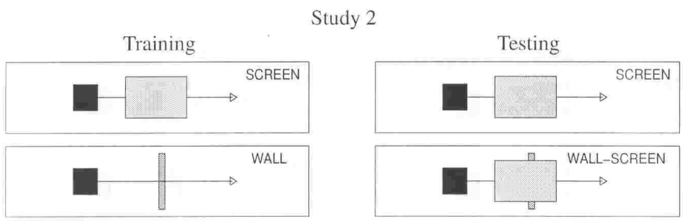

Figure 4:
Training and test events presented to OCM in study 2. A thinner wall was included representing a wall that has been moved back. The block passes in front of the wall. (from : (Schlesinger and Barto, 1999))

sults show that placing back the wall reduced OCM's tracking latency in the wall-screen trial compared to the wall-screen trials in the first experiment. However there is an difference between OCM's anticipatory tracking in the screen and wall-screen condition. A close analysis shows that in the 6 out of 50 runs, the tracking of the block was completely interrupted by the presence of the partially occluded wall. However, in the remaining runs, the differences between screen and wall-screen tracking latencies was .23 time steps. Therefor we can conclude that the wall did not disrupted OCM's anticipatory tracking, and that in both experiments OCM learns to use the wall and the screen as a cue for perceptual action (Schlesinger and Barto, 1999). In a third experiment OCM's network is extended with 20 input units that are connected with recurrent connections from OCM's hidden layer (Schlesinger and Barto, 1999). This provides OCM with a functional memory of previous interactions with the environment (Beer, 1996; Schlesinger and Barto, 1999). In this experiment, the wall is totally occluded and can no longer serve as a perceptual cue(Figure 5). When testing, it seems that OCM does not take

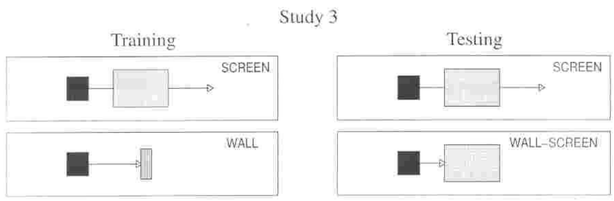

Figure 5:
Training and test events presented to OCM in study 3. A short wall was included wich was fully occluded by the screen during wall-screen trials. (from : (Schlesinger and Barto, 1999))

the wall, once occluded, into acount. It fails to use its memory of the short wall. This is because there is no pressure in the learning trials to use memory (Schlesinger and Barto, 1999). In the screen trial OCM learns to use the screen as a perceptual cue to anticipate the object reappearance.During the wall trial no memory is needed. The results of this experiment show that OCM can quickly learn a set of optimal tracking strategies for following a moving object. Also it shows that it anticipates the outcome of a new, partially occluded, causal event, but not a new fully occluded event (Schlesinger and Barto, 1999). Berthier et all in Schlesinger and Barto (1999) describes a series of experiment with 9-month-old infants that are comparable to experiment 1 and 3 of Schlesinger and Barto (1999). When comparing both results one can see that OCM provides a close qualitative fit to the performance of human infants (Figure 6). Like human infants, OCM uses the partially visible wall as a cue, but not the fully occluded wall, to guide its tracking behavior. An important implication of these experiments concerns the role of internal states. While most developmental researchers assume that infants operate on mental representations when objects are occluded or out of sight, OCM shows that “tracking an occluded target relies on sensory-motor rather than representational strategies for anticipating the target” (Schlesinger and Barto, 1999).

5 Conclusion

This paper started with a brief history of Artificial Intelligence, which was mainly dominated by computational-representational approach. As a reaction against this formal approach of cognitive behavior a new research paradigm arose, embodied cognitive science. With the rise of embodied cog-

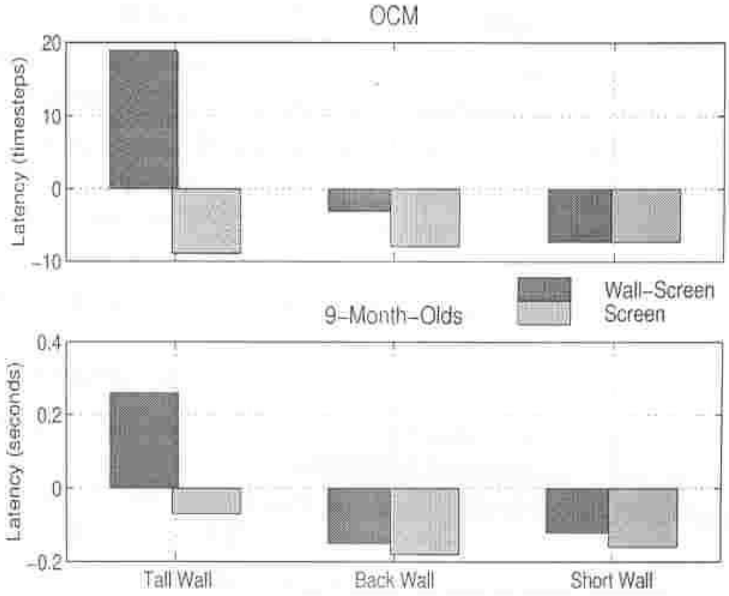

Figure 6:
Mean tracking latencies in the test phase of studies 1-3 for the OCM (top panel) and the 9-month-old infants (bottom panel) (from : (Schlesinger and Barto, 1999))

nitive science the debate concerning representations was re-opened, and led to a discussion between representationalists and anti-representationalists. Traditional A.I. see, internal representation as, symbolic or picture like complete representation of the external environment, whereas embodied cognitive science rejects this idea. In this paper internal states are introduced. One can see them as a set of internal variables with the function of carrying specific types of information. For example, in neural nets, these internal states can be seen as activities on nodes that, together with the weight connections, carry information about the environment and appropriate behavior. Although the difference between internal representations and internal states is not always clear, they both have the function of carrying information from the environment. The main differences are that; 1. the latter does not use symbols as complete models of the external environment and 2. internal states do not undergo explicit rule governed transformations. Perhaps more important than the discussion whether or not internal states are some sort of representations, is that internal states augment the embodied and cognitive framework and creates the opportunity to discuss and reason about situated models without the restrictions of the symbolic representations used by cognitivists. Another point of discussion is when systems have internal states or whether they make use of them? According to Beer and Clark, all kinds of systems can have internal states, even simple sensory-motor couplings in reactive agents. Whereas Nolfi states that internal states play a comparatively limited role (or no role at all) in reactive agents and states that internal states refer mainly to properties of non-reactive agents. However Beer makes a distinction between reactive and non-reactive systems on basis of the property of containing history of recent interactions with the environment. From the above I support Beer and Clark' vision in that, 1. all kinds of systems can have internal states whenever their function is carrying information about the environment and the behavior 2. the distinction between reactive and non-reactive systems lies in their ability to have a history of recent interaction with the environment.

The second part of this paper shows that the future of embodied and situated models in explaining biological behavior is promising. Where traditional models are good at explaining high-level cognitive tasks as, playing chess, they underestimate the importance of the behavioral context. I agree with Webb that the strength of embodied and situated models of cognition is that they are useful to test hypotheses about mechanisms of behavior, whenever this behavior is seen as a result of continuous interaction between body and environment.Section 4 states that embodied and cognitive models better fit real behavior than traditional model do. By means of two concrete examples, I showed to what extend these embodied and cognitive models can help in explaining biological behavior and psychological phenomena. Gibson's theory of direct perception revives in O'Regan and Noë sensory-motor approach to vision. The main difference in both views is that Gibson states that invariant are provided only by the environment whereas O'regan and Noë believe that the invariants lie in the retinal stimulation and the knowledge of a system about sensory-motor contingencies. O'regan and Noë resolve hereby the problem of Gibson's approach of how these invariant are being detected by the system. In the second research, from Schlesinger, is shown how embodied and situated models can help to explain, understand and provide new insights to accepted theories in psychology. Modeling causal perception as a sensory-motor process provides us new insight and help psychology in forming new theories.

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