Petitagé: A Case Study in Developmental Robotics

Georgi Stojanov

Computer Science Department
Electrical Engineering Faculty
Sts Cyril and Methodius University in Skopje, Macedonia
geos@cerera.etf.ukim.edu.mk

Abstract

In the present paper we describe several autonomous agent architectures developed in the last 5 years, and inspired by mostly by Piaget's genetic epistemology. In the introduction part we give an overview of the developments in AI and robotics after the behaviorist turn in the mid '80s and propose a tentative taxonomy of the approaches that followed according to their treatment of representation. Then we give a brief history of our autonomous agent architecture called Petitagé, tracing its roots from Tolman's to Piaget's works. We describe in detail the schema mechanism, proposed as a way of autonomous environment model building. In the concluding part, we comment on several works from the last 10 years which we consider to be of particular interest to this, developmental branch of robotics and AI.

1. Introduction

In a paper presented 1996, at the 3rd World's Behaviourist Congress, and entitled "AI (re-) discovers behaviorism and other analogies" (Stojanov et al., 1996a) we related the situation in AI in the mid 80's to the situation in psychology in the '30s, when the so called "physics envy" led to the rise of behaviorism. The school of behaviorism discarded the method of introspection because it dealt with hypothetical mental constructs (internal models of reality in men/women) that couldn't be subjected to objective (third person view) verification. What was observable was the *behavior* of the subject under inspection, hence the behavior and the influences of the various stimuli on it, was considered as the proper object of interest for the *scientific* psychology. In the mid '80s Rodney Brooks[1] gave a substance to the feeling (which was in the air) that *something* was deeply wrong in the dominant approaches in AI and robotics. Namely, although almost everybody would agree that the long-term goal of robotics and AI, is to design physical artifacts that exhibit intelligent behavior in an environment, since the inception of those fields, research was grouped around isolated topics considered of particular importance: representation (of knowledge, of environment), planning, search algorithms, and so on. Sure enough, there were attempts to combine all this in a single robot (e.g. Nilsson et al.'s Shakey, Nilsson, 1984) but the results were far from satisfying. Shakey's performance in specially designed for it environments didn't meet the expectations, and experiments with Shakey and its salon-type descendents in unstructured environments were simply out of question. Brooks response (Brooks, 1986) to this situation was a radical one. He put forward the claim that we don't need elaborated internal models of the environment. Instead of dealing with their maintenance and adequacy, what we should care for is the *behavior* of the agent in the real world, in environments not created especially for our artifact. Instead, the designer should choose the proper sensors and actuators and connect them with a bit of "clever engineering" to achieve desired behavior (the visible outcome). The mentioned similarity, perhaps, stops there ("No, I'm not a behaviorist!", Brooks, *personal communication*) since Psy-behaviourists, by the nature of their object of study, concentrated on the issues of stimulus and operant identification, situation definition, and the like. The behaviorist branch in AI, on the other side, working from "inside" adopted a methodology of producing overall behavior by combining basic behaviour modules. However, in what followed this initial turn, AI-behaviorism embraced *reinforcement learning*, the basic behaviorist methodology in *learning* research. In the conclusion of the "AI (re-)discovers behaviorism and other analogies" we have predicted that it was to be expected the analogy between AI and psychology to continue and that we were to witness some kind of cognitive revolution in AI and robotics, as well as consideration, appreciation, and even application of the works in developmental and, eventually, social psychology[2]. Well, it seems that it is happening now. In the next section, we describe the architecture for autonomous agents proposed in 1996 and called Petitagé. Before that, we would like to give some context giving an overview of the situation in AI after the behaviorist turn.

Taking behavior as a proper level of abstraction, in a later paper (Brooks, 1991) Brooks writes:

> There are no variables [...] that need instantiation in the reasoning process. There are no rules which need to be selected through pattern matching. There are no choices to be made. To a

[1] Brooks, certainly, was not the first one to deal with simple machines with emergent complex behavior, see for example (Walter, 1953; Braitenberg, 1967; Arbib, 1985). But Brooks was speaking with the language of the AI community

[2] For another perspective on parallels between AI and psychology see (Balkenius, 1995).

large extent the state of the world determines the action of the Creature.

In his *subsumption* architecture, all of the modules have access to particular *aspects* of the world via the sensory system, and simply read the sensors to find out the state of the world. A system designed according the above-quoted principles could not account for any type of learning since, if there are no variables in the system there is no way to change the behavior of the Creature in the sense of including past experiences in the current behavior. It is confined to the reactive type of behavior exclusively determined by the environment. Answering to this type of criticism he says that for the time being, they aim to an insect level of intelligence and implement the so called "learning by instinct". The hope is that by adding more and more levels complex intelligent behavior will somehow emerge. He compares his research program to the evolutionary process and under the section entitled "The future" in the same paper he writes:

> Only experiments with real Creatures in real worlds can answer the natural doubts about our approach. Time will tell. (Brooks, 1991).

Well, evolution *did* happen and in what follows will mention few "species branches". After the initial successes of the original subsumption architecture, it was soon realized that tasks like navigation and other tasks more complex than obstacle avoidance or wall following, *some* representation was indispensable. Hence, in the subsequent period, various representation systems were introduced. Below, we give a tentative taxonomy of them, according to their treatment of representation:

a) **pure reactive systems**: strictly behavioral systems with no central representation at all (e.g. Brooks, 1986; Maes, 1989, 1991); these architectures mainly differ in the way the behavioral (or competence) modules are connected;

b) **reactive system plus some memory structures**: in addition to the behavioral modules, agents are equipped with some (usually, uninterpreted) memory structures: these memory structures *are* some kind of representation, or better said, internal state which allows introduction of some kind of learning more complex behavior (e.g. Arkin, 1989; Watkins, 1989)

c) **eclectic architectures**: here, researchers simply took the behavioral modules as some gadgets to be attached to the otherwise *deliberative* agent architecture (e.g. Georgeff and Lansky, 1987; Mueler et al, 1994)

d) **interactionist approaches**: the main thesis behind this approach is that the representation has to emerge during agent-environment interaction; it depends on the particular embodiment of the agent (e.g. Drescher, 1991; Mataric, 1990, 1992; Indurkhya, 1991; Bickhard, 1993a; Basye et al, 1995; Tani, 1996; Stojanov et al 1995; Stojanov, 1997; Stojanov&Trajkovski, 1996; Stojanov et al, 1997a)

Most of the works from the class d) were directly influenced by various authors that were considered to be constructivist (in philosophy, in psychology) and particularly by the work of Jean Piaget.

2. The history of Petitagé architecture

The Beginnings

Petitagé /pee-ah-zhe/ was the first complete "cognitive architecture" that we've proposed (Stojanov et al., 1997a). It is based on its predecessor presented in (Stojanov et al 1995) which was a simple add-on mechanism to whatever control mechanism was used to control the behavior of some autonomous agent. This was a fairly simple idea, and the basic set-up is depicted in Figure 1. In Figure 1 a) we see the architecture of some autonomous system controlled by the "Control Mechanism". It computes whatever should be done given the particular sensory input. The augmented architecture has an Expectancy Module (EM) which maintains a table of triplets where one row has looks like this:

(Sensory_readings_at_t, Action_taken_at_t, Expected_sensory_readings_at_t+1)

Initially, the EM table is empty, and it is filled (it learns) as the agent behaves in some environment. After a while, it can predict the consequences of some action taken in particular context, and it takes up the control over the agent, speeding up its performance, since EM basically is a look-up table. However, when the certain expectancies are not met (e.g. cases where there are some changes in the environment) an "Expectancy break" signal is sent to the control mechanism and it computes the new output value for the actuators.

This architecture was inspired by Edward Tolman's *expectancy* construct (Tolman, 1948). Tolman, a neo-behaviorist has stressed the role of anticipation, and the need for some internal (mentalistic) structures to be introduced in the basic behaviorist S-R paradigm, in order to account for the results of some of his rats-in-mazes experiments (Tolman&Hoznik, 1930; Tolman 1932). Thus, the basic representational unit is the *expectancy unit* S_1-R-S_2, and it incorporates both sensory and motor information. So, if the learning agent is assumed to be able to build a network of such expectancy units, then various experimental results have natural explanations.

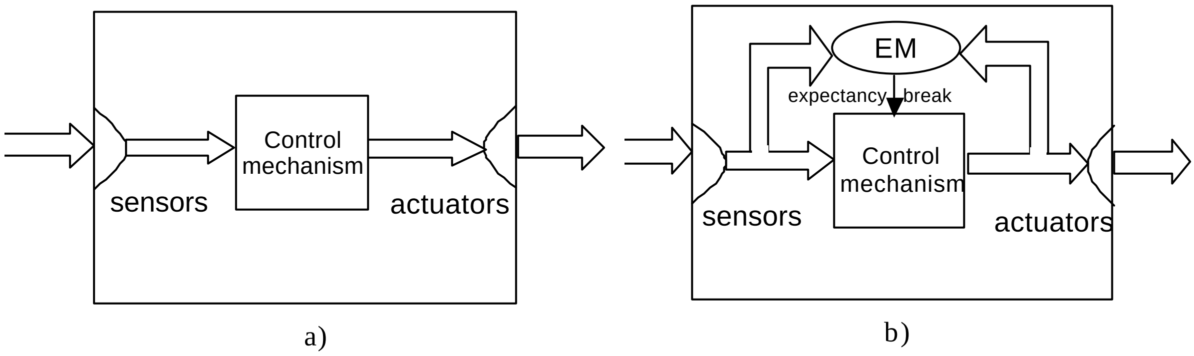

Figure 1 a) Original architecture for some autonomous agent; b) architecture augmented with the Expectancy Module (EM). See text for explanation. (Adapted from Stojanov et al 1995)

The Basic Petitagé Architecture

The next challenge was how to account for situations where different places the agents is found at, collapse into the same sensory image S (e.g. if the agent is facing a corner of the room, which corner is that?) The problem, known as *perceptual aliasing* problem is a common one. For example, in an article (Barto *et al*., 1995) it was shown that majority of *reinforcement learning* (RL) algorithms are properly treated within the dynamic programming framework. RL methods which use dynamic programming as mathematical framework, require that environment be represented to the agent via some *set of distinct labels* (i.e. different "S"s for every place). This puts constraints the domains where such methods could be used. In our opinion, the major problem is not *learning* the path to the goal if you have a model of the environment given as an implicit or explicit graph, but, namely, to autonomously *come up* with such a representation.

Jean Piaget's genetic epistemology (Piaget, 1954, 1970) and the wealth of experimental data and theoretical musings (e.g. Piaget, 1977; Piaget&Inhelder, 1978) looked to us as a natural departing point. Stated in a nutshell, and in today's terminology, his theory of cognitive development in humans is a process of a) spontaneous execution of inborn sensory-motor schemas b) building partial ordering in this space of modified, and newly formed schemas, as a result of the processes of assimilation and accommodation; c) interiorization of these operations by the acting agent. Naturally, central place in our cognitive agent architecture (Figure 2) that we introduced in (Stojanov et al, 1997a) is given to the notion of schema.

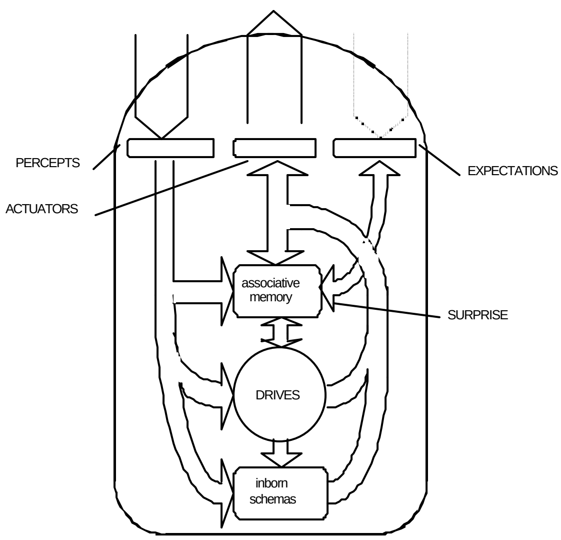

Figure 2 The basic architecture of Petitagé.

In our case it means something quite specific, namely the schema is *a sequence of elementary actions* that an agent is capable of performing. For example, if the $A=\{a_1, a_2, ..., a_n\}$is the set of elementary actions that the agent is capable of performing, a possible schema is $s= a_2\ a_1\ a_5\ a_7\ a_1\ a_1\ a_1$. With P we can denote the set of all different sensations (percepts) $P=\{p_1, p_2, ..., p_j\}$. One concrete example: some agent might be able of performing 4 elementary actions (go forward, go backward, go left, go right) in which case A={f, b, l, r}. If we suppose that it has 12 sonars each with 10 different levels of output, and a sensor for detection of the goal place (e.g. yes-energy, no-energy) than the cardinality of P would be $2*10^{12}$. Below, we explain how the agent can build useful environment model using our schema mechanism. Let $S= a_i.a_k. .... a_m$ be a string composed of the elementary actions which is characterized by its length and the relative ordering of actions. We will call S an *inborn schema*. When in *learning mode* the agent tries to execute S.

Because of the environmental constraints (see Figure 3 for 2 examples of 2D environments), when trying to execute some schema, only certain subsequences from the original schema will actually be performed. These subsequences are called *enabled schema instances*. For example, the initial inborn scheme S=ffffllffr will degenerate to $S_{enabled}$=fffff when the agent is trying to perform the inborn schema in a corridor. The map is then build out of the enabled schemas complemented with the percepts recorded on the way. Thus, the environment unfolds its structure to the agent via the subset of the enabled schema instances. The agent memorizes pairs of consecutive schema instances complemented with their respective perceptual sequences (that is, the strings of percepts perceived during schema execution). We call these pairs *expectancy constructs*. A *goal* is introduced to the agent

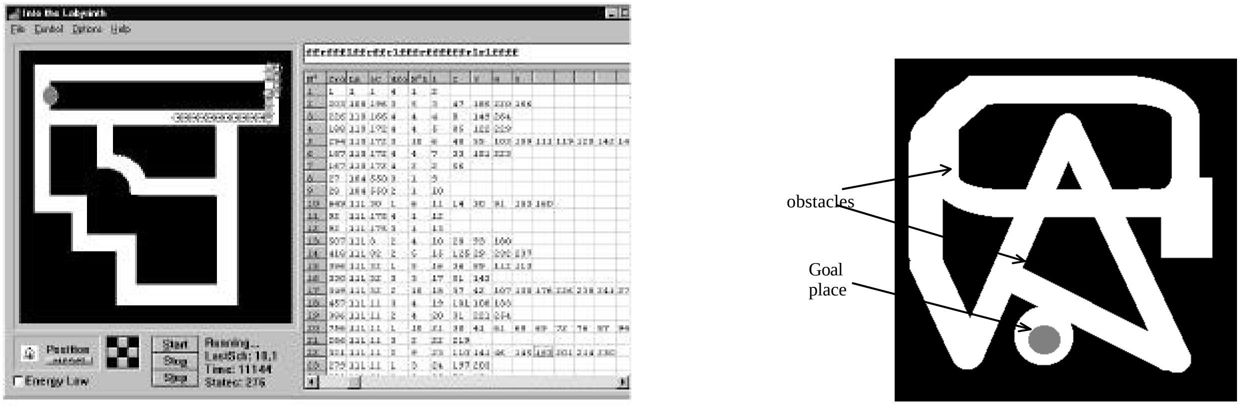

Figure 3 Simulation software screen snapshot, and two examples of 2D environments.

when some of its *drives* is active. A drive is satisfied when certain type of percept is experienced. How far is some expectancy from a goal, determines its *emotional context* for that particular drive (Figure 4) and this is the basic building block for representation of the environment.

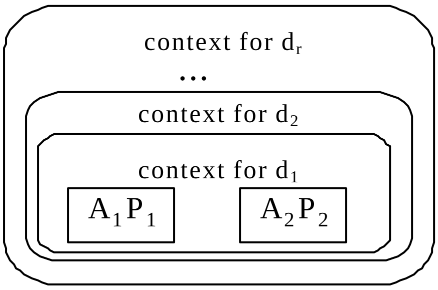

Figure 4 The basic building block for elements of the environment model in Petitagé; Ai and Pi are (respectively) strings of elements of A and P; depending on what drive is active, the appropriate emotional context is considered relevant for the goal.

Thus, the associative memory stores links of the following form link(A1P1, A2P2, D), where AiPi are concatenations of enabled schema action sequences with the accompanying percept strings, and D=(d1, d2…dn) is a vector storing essentially the distance to various goals. An example of environment model for some given agent-environment pair is given in Figure 5. Once this representation is learned, the agent proceeds as follows: it tries to execute the inborn schema; depending on the schema which is actually executed, it situates itself in the environment (i.e. chooses one (or more) left hand AP string); then (depending what drive is active, i.e. what goal is to be attained) the agent executes the enabled schema indicated with the right hand AP string with minimum value for di (the particular goal). We have given an algebraic model for this architecture in (Stojanov et al, 1997a; and more detailed version in Stojanov, 1997) and have demonstrated how perceptual aliasing problems is successfully tackled (Stojanov et al, 1997b, c.). In (Stojanov&Trajkovski, 1996) we discussed classes of environments which are learnable with this approach.

3. Adding More Structure in Schema Space

Agents built on the basis of the architecture described in the previous section, successfully solved navigational problems where, say, classical reinforcement learning (RL) architectures were helpless because of the perceptual aliasing problem. However, this was not the main intention with this architecture. The idea was to leave the task of environment model building to the agent itself, which we consider to be far more important. Further refinement of this basic model was to look for regularities in the stream of enabled schemas. As a higher level of abstraction, we have added a mechanism for detection of *cycles* in the stream of enabled schemas. A cycle is detected when the same sequence of enabled schema accompanied with same perceptual strings is encountered for more than n times where n is heuristically set big enough constant. When in cycle, and having completed an enabled schema, the agent can decide not to follow the actions dictated by the next enabled schema but make a random action instead, and, maybe, end up in a different cycle. The action is then memorized as connecting those two cycles. We can depict the situation with the Figure 6.

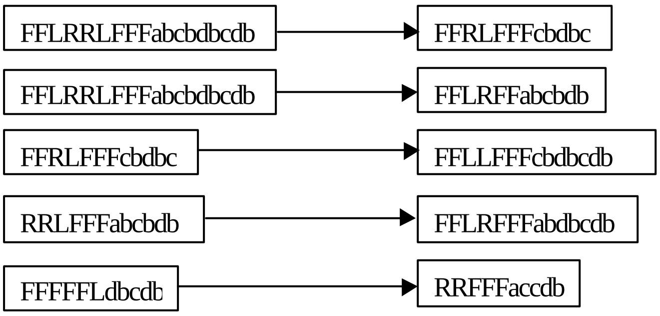

Figure 5 A portion of internal environment model for given environment-agent pair; D values are omitted for clarity; actions are denoted with capital, and percepts with small letters.

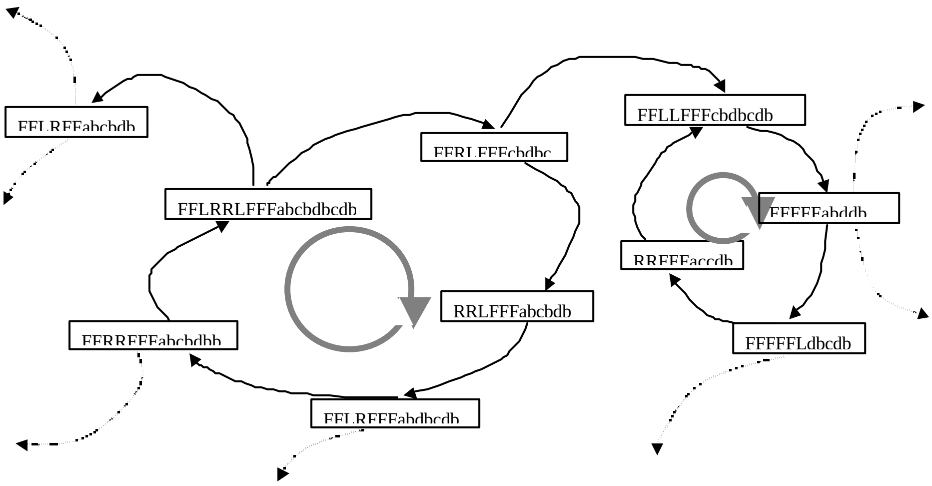

Figure 6 Discovering cycles in the sequences of activated enabled schemas

The rationale behind this is that for a given (finite) environmental niche and given inborn scheme and initial position, the agent will eventually go into a cycle while trying to perform the inborn schema. Thus, we can think of this process as introducing additional structure in the schema space by grouping several enabled schemas into cycles, and by connecting the cycles with links representing actions. The situation is depicted in Figure 7, and the new level of hierarchy can be seen as level of proto-concepts that are used to describe the environment and this is an ontology intrinsic to the agent (determined by its sensors, actuators, inborn schema, and the environmental constraints). Note that actions between cycles are reversible, and the agent can easily switch among cycles. Some experimental results and philosophical implications are discussed in (Stojanov, 1999, and 1999a). One can easily imagine an extension of this procedure with introduction of further layers in the hierarchy: the next level to be added would be a level where cycles of proto-concepts are detected, and so on. Actually, this way of looking onto the cognitive development of an agent may be a unifying framework of treating Piagetian phases (e.g. Indurkhya, 1991). Adopting this view, we have constructed some experimental set-ups for artificially inducing extra cognitive levels in human subjects (Stojanov&Gerbino, 1999b; Stojanov et al., 1999c).

Currently we are working on a physical realization of our architecture. This particular implementation, called Lucienne, memorizes the sequences and cycles using recurrent neural network, and it is based on the HandyBoard controller developed by Fred Martin (Martin, 2000).

4. Concluding Remarks

Above, we have tried to present some of our research in developmental (epigenetic?) robotics in the last 5 years or so. In the introduction, we gave a tentative taxonomy of approaches to the treatment of internal representation in autonomous agents in the period that followed the behaviorist turn in AI and robotics. This is important, since the treatment of representation determines one's construal of *learning* and *development*. Our approach, which we classified in the interactionist group was inspired mostly by the work of Jean Piaget. Given the limited space, we cannot do just to other researchers in AI and robotics who took Piaget's work as inspiration, by explaining their work here and comparing it to ours. However, we will try to briefly mention some of them.

Gary Drescher's work (Drescher, 1991) is, to our knowledge, the most elaborated architecture directly inspired by Piaget's theory. Central place is, sure

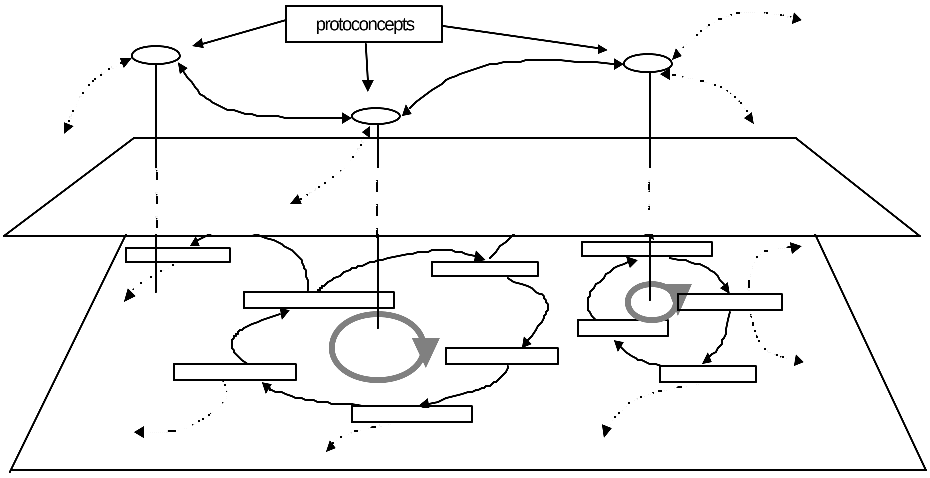

Figure 7 Introducing additional structure into the schema space; cycles are detected and connected with reversible actions; see text for explanation.

enough, given to the notion of schema, which is formalized as a triplet *context-action-result*. Figure 8 a) shows an example of such a schema which says that if the hand is in front of the mouth moving it backwards results in feeling a touch on the mouth.

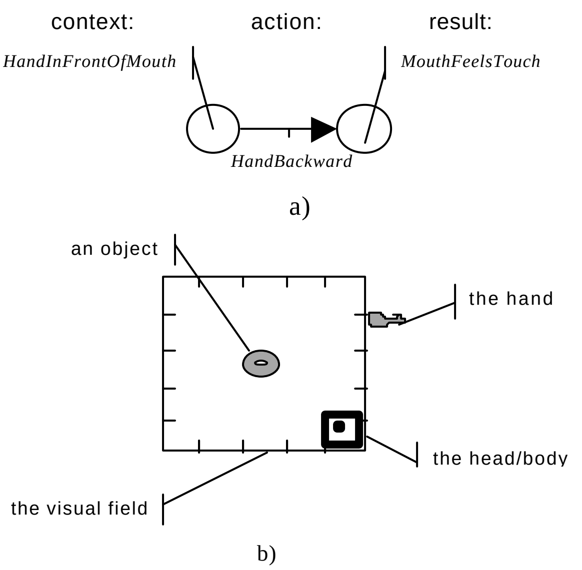

Figure 8 a) An example of Drescher's agent elementary schema; b) the simulated world of Drescher's agent; visual field moves relative to the body; here it encompasses the body and an object but not the hand

You can see that the context is described as (Boolean combinations of) propositions about the state of the world, which are true or false (on or off). The mentioned world is the visual field of the agent which moves relatively to the simulated body and hand (Figure 8 b). Initially, the agent has few schemas whose the context and result fields are empty. The *schema mechanism* has a learning facility called *marginal attribution*. Using this facility the agent learns a model of its environment by learning the effects of different actions in different contexts. This is done by extensive calculation of the *all possible* cross-correlations (among the possible contexts, actions, and results).

In his book "Metaphor and Cognition: *An Interactionist Approach*" Bipin Indurkhya (Indurkhya, 1992) proposes an algebraic model of analogical and metaphorical thinking. He stresses the importance that this problem should be treated within a general cognitive architecture. Indurkhya proposes a cognitive system where the central place is given to the notion of *conceptual network*. This is a new name for the Piaget's schemas. Using different conceptual networks, the agent can impose different interpretations of the incoming perceptual input. Another important thing is the grouping of different actions into same classes if their effect upon an object is the same. We do sympathize with Indurkhya's views and indeed our ideas for algebraic formalization originate in his work. On the other hand, he doesn't discuss the question of learning at all. That is, he says nothing as *where* from and *how* those conceptual networks come from.

Mark Bickhard's work in theoretical AI and robotics seems to be the most elaborated *interactionist* theory partially influenced by Piaget's theory. Although criticizing Piaget's model of perception since it involves straightforward sensory encodings in (Bickhard&Terveen, 1995) they state "his [Piaget's] constructivism is an essential part of understanding how the world is represented… Piaget's constructivism provides the skeleton for understanding this [cognitive] development". Some of Bickhard's ideas most relevant to AI and robotics can be found in (Bickhard, 1993, 1993a).

Although without explicit reference to Piaget, some early work of Mataric (e.g. Mataric, 1992, 1990) can be described as very Piagetian in spirit. For example, her Toto robot, actively explores the environment looking for regions that look the same in the sense that the perceptual input remains the same while some particular action is performed. Thus, the environment is partitioned into regions described with $a_i{*}p_j{*}$ (i.e. strings of same actions concatenated with same perceptual input) and the environment model consists of the links among these regions (link(a_i*p_j*, a_m*p_n*)).

Another approach, very constructivist and without explicit pointers to Piaget's work is presented by Tani in (Tani, 1996).

Cohen and his colleagues in (Cohen et al, 1996) present their simulated agent Neo whose learning mechanism is very similar to Drescher's marginal attribution.

Concluding this paper, we can safely say that there is an increasing recognition of the relevance of Piaget's work to modern AI and robotics research. In our opinion, his ideas should be complemented with the recognition of the importance of the social reality (where linguistic communication is comprised) in the development of the cognitive agent. Although Piaget talks about imitation as a kind of *external representation* which is to be internalized, as well as about other persons being one of the first "objects" of whose permanence the babies become aware (Piaget, 1970), he is rightfully criticized for essentially treating the developing agent as an isolated entity. *Isolated entity* here means that he often neglects the role of social interactions and language especially, in the cognitive development. Researchers in AI and robotics have already recognized the importance of social interactions as a source of additional constraints and ideas in the construction of intelligent artifacts (e.g. Dautenhahn, 1997, 1998; Breazeal, 1998). There is also a growing interest in entertainment robotics (Sony's AIBO, iRobots My Real Baby, etc.) fueling the research in socially intelligent robots.

References

Arbib, M.A. (1985) *In Search of the Person*, The University of Massachisetts Press.

Arkin, R. (1989) "Motor Schema-Based Mobile Robot Navigation", International Journal of Robotics Research, 8(4).

Balkenius, C. (1995) *Natural Intelligence in Artificial Creatures*, Lund University Cognitive Studies 37.

Barto, A. G., Bradtke, S. J., Singh, P. S. (1995) "Learning to act using real-time dynamic programming", *Artificial Intelligence*, No. 70.

Basye, K., Dean, T., Vitter, J. S. (1995) "CopingWith Uncertainty in Map Learning", *Machine Learning.*

Bickhard, M.H., Terveen, L. (1995) *Foundational Issues in Artificial Intelligence and Cognitive Science: Impasse and Solution*, Elsevier Science Publishers.

Bickhard, M.H. (1993) "Representational Content in Humans and Machines", *Journal of Theoretical and Experimental Artificial Intelligence*, 5.

Bickhard, M.H. (1993a) "On Why Constructivism Does Not Yield Relativism", *Journal of Theoretical and Experimental Artificial Intelligence*, 5.

Braitenberg, V., (1967) "On the Use of Theories, Models and Cybernetical Toys in Brain Research", *Brain Research*, 6.

Breazeal, C., Velasquez, B. (1998) "Toward Teaching Robot 'Infant' Using Emotive Communication Acts", in 'Socially Situated Intelligence: Papers from the 1998 Simulated Adaptive Behavior Workshop.

Brooks, R. A. (1986) "A Robust Layered Control System for a Mobile Robot", IEEE Journal of Robotics and Automation, RA-2, April.

Brooks, R. A. (1987) "Intelligence Without Representation", Preprints of the Workshop on Foundations of Intelligence, MIT: Endicott House.

Brooks, R. A. (1991) "Intelligence Without Representation", *Artificial Intelligence*, No. 47.

Brooks, R. A. (1991a) "How to Build Complete Creatures Rather than Isolated Cognitive Simulators", in Kurt VanLehn (ed.) Architectures for Intelligence, The Twenty-Second Carnegie Mellon Symposium on Cognition, 1991a.

Cohen, P.R., Oates, T, Atkin, M.S. (1996) "Preliminary Evidence that Conceptual Structure Can Be Learned by Interactingwith an Environment", AAAI Fall Symposium on Embodied Cognition and Action, TR FS-96-02.

Dautenhahn, K. (1997) "I could be you – the phenomenological dimension of social understanding", Cybernetics and Systems, 25(8).

Dautenhahn, K. (1998) "The Art of Designing Socially Intelligent Agents: Science, Fiction, and the Human in the Loop", Applied Artificial Intelligence Journal, Special Issue on Socially Intelligent Agents, 12 (7-8).

Drescher, G. (1991) *Made-Up Minds*, MIT Press.

Georgeff, M.P. and Lansky, A.L. (1987) "Reactive Reasoning and Planning", Proc. Sixth National Conference on Artificial Intelligence (AAAI-87), Seattle.

Indurkhya, B. (1992) *Metaphor and Cognition, An Interactionist Approach*, Kluwer Academic Publishers.

Maes, P. (1989) "The dynamics of action selection", Proc. IJCAI-89. Detroit.

Maes, P. (1991) "The Agent Network Architecture (ANA)", SIGART Bulletin, 2(4).

Maes, P. (1991) Designing Autonomous Agents: Theory and Practice from Biology to Engineering and Back, MIT Press, Cambridge.

Martin, F. (2001) *Robotic Explorations: An Introduction to Engineering Through Design*, Addison-Wesley, 2001.

Mataric, M. (1992) "Integration of Representation Into Goal-Driven Behaviour-Based Robots", IEEE Transactions on Robotics and Automation, Vol.8, N.3.

Mataric, M. (1990) "Navigating With a Rat Brain: A Neurobiologically-Inspired Model for Robot Spatial Representation", in J. A. Meyer & S. Wilson, eds. From Animals to Animats, International Conference on Simulation of Adaptive Behaviour, The MIT Press.

Mueler, J.P., Pischel, M., Thiel, M. (1994) "Modeling Reactive Behavior in Vertically Layered Agent Architectures" in Wooldridge, M.J., Jennings, N.R. (eds.) "Intelligent Agents", Proc. Of the ECAI-94 Workshop on Agent Theories, Architectures, and Languages, Amsterdam.

Nilsson, N. (1984) "Shakey the Computer", SRI Tech report, SRI Menlo Park, CA.

Piaget, J. (1954) *The Construction of Reality in the Child*, Basic, New York.

Piaget, J., *Genetic Epistemology*, Columbia, New York.

Stojanov, G. (1999) "Embodiment as Metaphor: Metaphorizing-in The Environment" in C. Nehaniv (ed.)

Lecture Notes in Artificial Intelligence, Vol. 1562, Springer-Verlag.

Stojanov, G (1999a) "A Model for Spatial Representation with Controlled Partitioning of the Environment", in the Proceedings of the Workshop on Learning and Perception in Robot Systems, Parma, Italy.

Stojanov, G., Gerbino, W. (1999b) Investigating Perception in Humans Inhabiting Simple Virtual Environments, European Conference on Visual Perception, Trieste.

Stojanov, G., Kulakov, A., Trajkovski (1999c) G., "Investigating Perception in Humans Inhabiting Simple Virtual Environments: An Enactivist View", Cognitive Science Conference on Perception, Consciousness and Art, Vrije Universitaet in Bruxelles.

Stojanov, G. (1997) *Expectancy Theory and Interpretation of EXG curves in the Context of Machine and Biological Intelligence*, PhD Thesis, University in Skopje, Macedonia.

Stojanov, G., Bozinovski S., Trajkovski, G., (1997a) "Interactionist-Expectative View on Agency and Learning", IMACS Journal for Mathematics and Computers in Simulation, North-Holland Publishers, Amsterdam, Vol. 44.

Stojanov, G., Trajkovski, G., Bozinovski, S. (1997b) "The Status of Representation in Behaviour Based Robotic Systems: The Problem and A Solution", IEEE Conference Systems, Man, and Cybernetics, Orlando.

Stojanov, G., Trajkovski, G., Bozinovski, S. (1997c) "Representation Vs. Context - A False Dichotomy: Introducing Intrinsic Representations", ECCS'97, Workshop on context, Manchester.

Stojanov, G., Trajkovski, G. (1996) "Spatial Representations for Mobile Robots: An Algorithm for Detection of Learnable and Non-learnable Environments", 1st Congress of Mathematicians and Computer Scientists in Macedonia, Ohrid.

Stojanov, G., Bozinovski, S., Simovska, V. (1996a) "AI (Re)discovers behaviourism and other analogies", presented at the 3. Int. Congress on Behaviourism and Sciences of Behaviour, Yokohama.

Stojanov, G., Stefanovski, S., Bozinovski, S. (1995) "Expectancy Based Emergent Environment Models for Autonomous Agents", 5th International Symposium on Automatic Control and Computer Science, Iasi, Romania.

Stojanov, G. (1994) "The Fourth Dialogue Between Hylas and Phylonus about the End of a Science or George Berkeley the Virtual Realist, Vindicated", in S. Bozinovski (ed.) *The Artificial Intelligence* (in Macedonian), GOCMAR, Macedonia, (English version available at www.soros.org.mk/image/geos/providenceFACE.ps).

Tani, J. (1996) "Model-Based Learning for Mobile Robot Navigation from Dynamical System Perspective", Systems, Man, and Cybernetics.

Tolman, E.C. (1948) "Cognitive Maps in Rats and Men", Psychological Review, 55.

Tolman, E.C. (1932) "Purposive Behavior in Animals and Men", Appleton-Century-Crofts, New York.

Tolman, E.C.&Honzik, C.H. (1930) "'Insight' in Rats", University of California Publications in Psychology, 4.

Vygotsky, L.S. (1978) *Mind in Society*, Cambridge, MA. Harward University Press.

Walter, G. (1953) *The Living Brain*, Norton&Co, UK.