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A Survey of Research Works in Computer Science and Cognitive Science dedicated to the modelling of Reactive Human Behaviours

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Abstract

Modelling believable autonomous agents needs to take into account many different aspects from very different disciplines, ranging from cognitive psychology to mechanics. In this paper, we are focus on research work dedicated to the modelling of human decision in a reactive way which falls clearly in-between the biomechanical motion control of the activity and the rational and social backgrounds which motivate and shape the execution of such activities.

This paper presents different models introduced in computer science to model reactive human behaviours. Then it continues with the presentation of different theories from cognitive science about reactive behaviours. We conclude with a comparison of models introduced in computer science with theories introduced in cognitive science.

1 Introduction

Behavioural models have been introduced to study and design autonomous entities such as living beings or robots. In this report, we focus on anthropomorphic virtual characters, and we will compare different formalisms introduced in computer science over the last twenty years to theories proposed by cognitive scientists. In computer science, the goal in modelling human behaviours is not to reproduce the complexities of the human brain and body but to propose software architectures able to generate believable human behaviours in specific activity contexts. To model a human behaviour, it is necessary to address different issues, such as multi-sensory perception; memory activity; facial and bodily muscular control, including affective expressivity; intentionality; and action selection. In short, it is necessary to investigate the operation of various faculties that constitute together the human mind, always considering their relations to the body and the physical and social environment at large.

Complementing such study of general mechanisms underlying any human behaviour, the work should also be concerned with the study of human faculties in dedicated activities, such as navigating in a city; using a work instrument; or conducting a structured interview. The comprehension of human behaviours requires competences in fields as varied as the neurosciences; different branches of psychology; behavioural biology; and organisation sciences. There are two approaches regarding the study of human behaviour: the first one is system oriented and builds on results from the neural sciences looking at the brain activities of patients subjected to various stimuli, according to well defined operating protocols. The techniques used include brain imaging: PET (Positron-Emission Tomography), fMRI (functional Magnetic Neuro Imaging); or the measurement of electric activity: ERP (Event Related Potentials). It focuses mainly on concepts of signal transmission in networks, control, and state feedback. The second, more symbolic, approach consists in modelling human behaviour in a more abstract way by the way of modules, each of which describes a functional mechanism. These modules are possibly hierarchically organised and linked by sequencing and/or parallel relations.

None of the models proposed in either of the two approaches is completely satisfactory to model the human behaviour in its entirety. However, we are still more interested in the second approach, due to its more macroscopic vision and to its similarity with software component architectures. Indeed, our problem at hand is not to reproduce human intelligence but to propose a software architecture allowing to model credible behaviour of virtual anthropomorphic actors performing (and thereby evolving) in real-time in virtual worlds. These worlds ones can be very restricted, e.g. representing particular situations studied by psychologists, or even correspond to a full imaginary universe described by a scenario writer. In any case, the proposed architecture should mimic relevant human intellectual and physical functions.

Von Uexküll [71] defined the environment as the part of the outside world with which a human or animal body can naturally interact. The human body is in constant interaction with its environment by means of sensors and of effectors. The overview of the system is a perception-decision-action loop, with three different kinds of connection between action and perception. The first feedback from actuators to sensors is called homeostasis and designates the internal regulation feedback used by the body for the preservation of the biological parameters against variations of the ambient environment, whereas the second one stands for acquisition behaviour, which comprises actions driven by perception (e.g. turning the head to see something which expected to be next oneself). However, the most important loop corresponds to the interaction with the environment.

Concerning the processing unit between sensors and effectors, H. Mallot [43] introduces a classification into various levels of complexity, and illustrates four of them[1]. The

[1]Note how such modeling in the "reflex-arc" tradition is contrasted by a range of models emphasising the primacy of action of perception (see e.g. [20, 2, 53, 70]).

first level represents reflexes of attraction/repulsion type, which can be defined simply by an interconnection between sensors and effectors. The following level represents behaviour, which requires inter-neuron integration in hidden layers and which allows to describe manoeuvering requiring spatio-temporal integration. The third level deals with the plasticity of spatio-temporal integration, but this learning behaviour still remains completely determined by the state of the sensory data. The fourth level, dedicated to cognitive behaviour, does not depend any more on sensory stimuli only, but also on a currently pursued purpose.

In the following, we first present different models proposed in computer science before describing theories developed in cognitive science and identifying interesting links between these bodies of contributions.

2 Behavioural Models Proposed in Computer Science

2.1 First generation of reactive behavioural models

The models to be discussed in this section view the reactive layer as being in charge of the realization of simple behaviours that do not need to explicitly manipulate an abstract representation of the world. Historically, one can place the first efforts on reactive behavioural animation at the end of the 1980s, in particular with the article by Craig Reynolds on the animation of flocks of birds [55]. A first set of approaches was investigated in parallel in the literature, up to the middle of the 1990s, concerning the definition of the decision-making part of such behavioural models:

sensor-effector: This approach defines the behaviour of objects based on a set of sensors and effectors interconnected by a network of intermediate nodes transforming the transiting information [73, 68, 50]. This type of approach includes also neural network models [66]. The way an object behaves depends on the perception which it has of its environment and the way this perception is passed on through the network to the effectors which produce the movement of objects. This approach has the advantage of being able to generate a very important quantity of different movements (based on the given the set of parameters), but on the other hand remains at a very low level of abstraction. Furthermore, this kind of model functions like a black box in which it is impossible to modify even a single parameter without having to reissue the complete process of configuration. In addition, the percentage of good controllers decreases in an exponential way with the growth of the number of parameters to be taken into account; this approach is thus ill suited to the definition of complex behaviours.

behaviour rules: as the previous approach, the approach by rules of behaviour takes as input data information corresponding to a certain perception of the environment and produces control over the motion of objects as output. Here, the behaviour of objects is defined by a set of rules [55]. The possible behaviour of an object can e.g. be represented by a decision tree, with every branch representing a different behaviour. An action satisfying the conditions of the current environment will be chosen by the application of a tree traversal algorithm. Behaviours allowed by this approach are of a higher level of abstraction than the previous one. The heart of the problem in this approach lies in the weighing (i.e., ranking) of the various behaviours. The simplest solution consists in making an implicit choice on the order of rules, but this solution does not allow the specification of complex behaviours. Assignment of weights to the different subbranches of the tree enables not to privilege always the same rule; design of tree hierarchies considering expert knowledge allows to relate several concurrent behaviours, with the final choice staying at the upper level of the tree[18, 67].

finite automaton: the finite automaton defines the various possible sequences of behaviour [64]. Applicability of this approach hits a ceiling very quickly with increasing complexity of the behaviour to be modelled. Exemplifying a solution to this issue while remaining within the same paradigm, Booth et al. [10] demonstrate the modelling of the behaviour of a car driver using several statemachines, whose concurrent execution then needs to be coordinated.

A summary statement over this range of efforts is that they are specific models conceived to be applied to particular cases, in which objects and their environments are relatively simple and perception and action capabilities are limited. Besides, there is a big disparity in the behaviour allowed by the different approaches. Either the level of abstraction is very low and the only behaviours that may be specified are reflex-like ones (sensor-effector approach), or the level of abstraction is higher, but then the environment is necessarily reduced and has to be completely defined, and it is then the perceptions and actions of the entity that are of a very low level of complexity. These models remain in any case relatively simple, with limited fields of perception and action, and furthermore do not take the temporal aspect into account, even though it is usually essential.

2.2 Second generation, handling more complex reactive behaviours

To match the challenge posed by higher levels of decision-making complexity, it is necessary to handle continuous and discrete aspects collectively, to coordinate concurrent behaviours, and to manage their organizational structure. That is why the first two approaches presented were rather quickly abandoned in favour of approaches based on state-machines in parallel and hierarchical versions:

- stacks of state-machines (EPFL, Switzerland) [52];
- sets of communicating state-machines (PaT-Nets) (University of Pennsylvania, USA) [5];
- hierarchy of parallel state-machines (HCSM) (University of Iowa, USA) [4];
- parallel transition systems organized into a hierarchy (HPTS) (IRISA, France) [23].

This kind of approach is now also common in the animation and game industries. More recently, models have been proposed to handle uncertainty, either by using Bayesian programming[36] or decision networks[74], a generalization of Bayesian networks. Even if these models are hierarchical in their structure, they do not allow to manage the coordination between concurrent behaviours, as only pure parallelism without any relation between parallel decision networks can be covered.

As an example, let us look in more detail at the Hierarchical Parallel Transition System (HPTS). HPTS is a reactive behaviour description model combining state-machine and multi-agent approaches. Every state of every automaton is an *agent* possessing an internal state, being able to receive stimuli, and to emit new environmental stimuli in reaction. Any active state of the system receives a stream of input data, delivers a stream of output data, and possesses a continuous and discrete control. A state of the system is either a terminal state, or a composite state. G. Moreau [47] proposed an implementation of the HPTS model, including a programming language and a compiler allowing to generate equivalent C++ code. Each state has its own activity status, with three possible values: *active, suspended, inactive*, and dedicated functions are executed when the status changes: *begin, end, wait, resume.* The control parameters allow to influence the behaviour to be adopted by either external or internal decisions.

A filtering function manages the coherence of the actions proposed by the active states of the parallel sub-state-machines. When concurrent behaviours are proposed by different sub-behaviours, this function is in charge of making a choice and to deliver a unified behaviour to the superior layer. An automaton is always executed after its child, allowing to select a behaviour and to mix the propositions supplied by its sub-components. So, concurrent behaviours can work in parallel and be arbitrated. This model was successfully used to model the behaviour of car drivers and pedestrians [22, 65]. This language was then extended [21] to manage random choice between different possible behaviours with weighted rates and to manage also the reaction times between decisions and actions.

2.3 Competitive and cooperative approaches for action selection

2.3.1 Introduction

According to William Clancey [17], goal directed behaviours are not always obtained by inference or compilation: some actions may simply reproduce cultural motives while still others are coordinated without deliberation, just based on attention and adaptation. A person does not perform several tasks strictly in parallel; rather, several tasks take place by merging attentively several parallel interests. It is thus useful to offer a mechanism allowing to execute different behaviours in parallel without having to program the synchronization of their execution by hand. Moreover, while describing a behaviour it should not be necessary to take into account all the possible behaviours that may interfere with it, as this may evolve depending on the context. Two kinds of action selection algorithms meeting these requirements are the cooperative approach and the competitive approach.

2.3.2 Cooperation vs Competition

The cooperative approach allows combining several potentialities of action, whereas competition pursues only a single action out of all the potentially practicable ones. Because of the expressiveness of the combinations of the actions to be supported, the former approach is mainly based on the usage of arithmetical functions on quantitative data, whereas the latter approach typically determines the best action to realise in a given context through the use of cost functions coupled with information of a more qualitative nature.

HPTS supports both approaches through the notion of integration functions available at each level of the hierarchy. Integration functions are in fact programmable functions, and the programmer has the choice at each level to implement a competitive or a cooperative function, according to the nature of the behaviour to be handled.

2.3.3 Situation Calculus

In the competitive approach, one of the earliest formalisms employed to describe cognitive systems is situation calculus [46], which allows to reason about the world and its changes. The situation calculus allows the exploration of all the possible worlds that can result from the execution of one or many actions, starting from a given world state. Reasoning in the situation calculus is based on four concepts:

Situations: A situation describes the complete state of the world at a given time, through facts that describe the properties of the environment. These can be used to deduce further facts that either hold in the present or would hold in the future;

Fluents: Fluents describe properties of the world that can change with time. They are functions which take a situation as input and return the state of the property. Fluents can be used to describe an atomic fact or relations holding between objects in the environment;

Actions: Actions allow changing a situation as long as action-specific sets of properties termed preconditions can be verified to hold. An action modifies a situation to create a new situation, thus modifying the description of the world;

Knowledge: Knowledge can be gathered for example from the world through actions that describe perceptions, which allows reasoning at a rather high level of abstraction. This can e.g. enable the incremental gathering of partial information necessary to achieve a specific goal.

Using sound and complete inferencing mechanisms that build on these concepts, it is possible to derive all possible evolutions of a given world, and thus to infer correct sequences of actions suited to accomplish a specific goal. However, this approach suffers from one main problem, called the frame problem [58]: the fact that along with a specification of changes it is also necessary to explicitly describe everything in the world that does not change when an action is undertaken. Such a complete description is almost always impossible to achieve for real-world scenarios. To circumvent the frame problem, it is necessary to make the strong hypothesis of evolving in a completely closed world, i.e., to assume that everything not directly concerned by the action, remains unchanged.[2]. The Sit-

[2] See e.g. [57], Chapter 10 for an overview of more recent evolution of research on the frame problem (including the solution proposed by Ray Reiter [54] by decomposing it into sub-problems).

uation Calculus remains however a powerful mechanism for environments of limited size, where the author can have a good control over the impact of each action. J. Funge has proposed an implementation for virtual environments through the Cognitive Modeling Language (CML) [25], demonstrated with prey-predator examples. [26] provides an overview of the recent evolution of the GOLOG programming language defined in the situation calculus, on which Funge's work was based, to IndiGolog, capable of supporting high-level program specifications for reactive agents.

2.3.4 ASM: Action Selection Mechanism

Still concerning the competitive approach, action selection algorithms were proposed in the field of multi-agent systems, most being extensions of the Action Selection Mechanism (ASM) algorithm introduced by P. Maes[42]. We can quote the algorithm by V. Decugis and J. Ferber [19] that addresses the interesting problem of how to combine real-time reactive and planning abilities in the same model (in the particular case of robotics) in the tradition of the Brooksian Subsumption Architecture [11]. To this end, Decugis and Ferber proposed a hierarchical ASM in which the lowest levels concern basic reactive behaviours and the higher levels integrate behaviours of increasing complexity (in the same way as in the hierarchical parallel state-machine approach). At every level, a mechanism of arbitration must be used to choose among the actions proposed by the parallel ASMs.

B. Rhodes proposed another hierarchical extension of the ASMs called PHISH-Nets [56]. This model supports the use of parameterised actions and allows to define relations between actions which are either of conflicting type or of antecedent type. These models allow to perform reactive planning, but a main inconvenience concerns the requirement of an exhaustive specification of all possible interactions between actions. Furthermore, in these models circumstances demonstrably do occur, for which no (always valid) decision function can be specified.

2.3.5 ABL: A Behaviour Language

Façade, developed by M. Mateas and A. Stern [44] integrates in a single application the management of the structure of the dynamically evolving story, the control of the behaviour of two characters, and natural language processing for the interaction with a user interpreting the role of a visitor as the third character of the story. Grace and Trip, a computer-controlled troubled couple in their thirties, are the protagonists of the story modelled loosely after Edward Albee's *Who's afraid of Virginia Woolf*. The behaviour of the protagonists is defined by means of the reactive planner language ABL [45]. ABL supports the specification of behaviour coordination and further includes a resource reservation mechanism allowing a behaviour to request the use of a physical resource with a certain priority.

2.3.6 HPTS++

F. Lamarche [40] suggested automating the mixing of behaviours with respect to their relative importance, by using the cooperative approach. To illustrate the problem addressed in this work, let us take a concrete example: a person is in front of a table, she reads a book while drinking a coffee and smoking a cigarette. This sentence describes a behaviour that is relatively simple for a human being, however in term of behavioural animation, it raises a range of problems. On one hand, it consists of three *independent* behaviours which take place simultaneously: to read a document, to drink a coffee, and to smoke a cigarette. In the previous models, describing this type of composited behaviour is relatively difficult, as it is necessary to be able to rank the component behaviours so as to meet a certain number of constraints, such as not to drink the coffee while having a cigarette in the mouth, nor to manipulate the pages of the book while the hand holds the cup of coffee. On the other hand, in the coordination of these three behaviours described separately it is necessary to avoid the re-coding of specific behaviours dedicated to their simultaneous realization.

The objective is to be able to launch the sub-behaviours and to have them be executed together automatically according to the circumstances, the social, psychological, affective, and physical constraints of the virtual human. The biggest synchronization problems come from the use of the internal resources of the agent: the gaze, the hands, the feet, or more generally any dependence, physical or not, limiting the parallel execution of different behaviours. To reach the objective, three new notions were introduced within the HPTS model: resources, priorities, and degrees of preference, giving rise to the HPTS++ model[40]. The mutual exclusion of the use of resources allows to define what behaviours are compatible at all times. The priority is a coefficient which indicates the importance of a behaviour in a given context. This coefficient can characterise either the adequacy (activation) or the inadequacy (inhibition) of the behaviour in a given environment. The priority can be defined to dynamically change over time.

The degree of preference is a numerical value associated with each transition of a statemachine. This value allows to describe the tendency of the behaviour to use this transition when the associated condition is true. Thus, depending on its value, this coefficient has different meanings. If the value is positive, the transition favours the realization of the behaviour. If the value is negative, this transition does not favour the realization of the behaviour, but allows to describe a way to adapt the behaviour while releasing some resources needed by another behaviour or to coherently terminate the behaviour. A null value will not influence the behaviour.

This system allows to describe behaviours with all their adaptation possibilities at a fine grained level. Thanks to a mechanism of interblocking avoidance, the description of a new behaviour does not require knowledge of behaviours already defined. In this way, the coordination of all active behaviours becomes generic and automatic. A complete description of this automatic coordination algorithm is given in [40], with a full illustration by the example of the { *reader / drinker / smoker* } character.

2.4 Role-passing in Twig

Extending network representations to provide expressiveness of traditional symbolic reasoning systems, i.e., variable binding, without incurring significant performance penalties thus poses a difficult challenge of very high practical relevance. As discussed in [33], this issue can be approached by using a general inference engine for high-level problem solving, caching the results in a dependency network (as in the Soar system); building the network in a more general programming language, as with Nilsson's Teleo-Reactive approach [51] or with a GOLOG-like approach as discussed above; or building the network manually, facing exponential complexity problems as just mentioned in the case of the PHISH-Nets. A different strategy looks for ways to exploit limited versions of variable binding for purposes of high practical value. For example, the so-called deictic representation used in [2] drew inspiration from the limitations in tracking capabilities of the human visual system, and demonstrated successfully how within this special-purpose context central reasoning could be effectively relieved of the need of costly and overly generic exhaustive inferencing for perceptual object binding by fluently playing then-popular arcade games such as Pengo.

Along these lines, Ian Horswill points out how many reasoning tasks involve only a relatively small set of objects at a given time[3]. Drawing upon earlier work on robotic systems [34], he developed the technique of role passing, by means of which a limited subset of Prolog-like reasoning on unary predicates can be executed with extreme efficiency. This approach affords representation of prioritized goals, as required in scenarios such as discussed for the HPTS++ system and has been deployed in Twig[35], an open-source procedural animation system for interactive narrative applications. In Twig, each character maintains a

[3]One could note here a relation to the philosophy guiding the solution of the frame problem by virtue of the introduction of so-called successor state axioms, which likewise significantly constrain the search space in terms of the typically small range of effects of a bounded set of actions in an extended world.

small working memory of world objects, forming the basis for the use of role-passing as light-weight solution running at frame rate frequency for issues of subgoal sequencing and resource allocation (e.g., of the characters' eyes/gaze) between concurrent and competing tasks.

While certainly not a solution for all kinds of low-level information processing challenges, role passing can contribute to significantly improving the performance of virtual characters by removing expensive reactive responsibilities from general components such as generative planners. With its inspirations from architectural properties of natural cognitive systems, this effort points towards the topic domain of cognitive science theories, covered in the next section.

3 Theories proposed in Cognitive Sciences

The hierarchical nature of levels of behaviour is generally recognised today. For A. Berthoz [6], the complex problem of the motor control was solved in nature by a hierarchy of levels of control where each is applied on internal models of the system which precedes it[4]. The theory of control in behavioural psychology as described by R. Lord and P. Levy [41], takes up the principle of force-feedback loops, while spreading it to all behavioural processes,

[4]Even so, we do acknowledge the existence of *deep connections* e.g. in the human nervous system, which connect higher level directly to the lowest ones and to sensors and effectors (Gary Berntson, personal communication).

from the simple task of visual servoing to the regulation of social behaviour. For Lord and Levy, the generality of retroaction loops for the description of behaviour results from the hierarchical nature of the systems of control, even if the nature of the activities of control can be very different according to the levels. The common point between all these levels lies in the comparison between a perceived state and an expected state and in maintaining the error within acceptable limits. Every level knows only the immediately lower level and receives only errors already elaborated by internal models which compare a wished state to a real state.

The brain contains several schemas of the body (mechanisms of simulation of action) that are independent from the real body itself [6]. The superior organs which take decisions do not necessarily work by arranging sensory information directly. These centres know only the state of the inferior levels of execution which contain models of the levels which they control, and, in particular, which estimate the errors between what they imposed and what is executed.

Lord and Levy [41] stated the hypothesis that control of the human processes is produced by a mutual interaction between two mechanisms: *top-down* and *bottom-up*. Top-down control is abstract and strongly connected to the current intentions and to established plans, whereas bottom-up control is more guided by data, i.e., conveys the information supplied by the perceptive system, so as to recognise any conflicts. The ascending regulation is a necessary complement to the downward control mechanism, to assure that the cognitive system will note and answer correctly physiological and psychological demands. Nevertheless, the detection of conflicts at the hierarchical level corresponding to the management of tasks should not create too much additional cognitive load to that resulting from symbolic reasoning. On the other hand, conflicts between upstream and downstream processing are assumed to be capable of interrupting thought to redirect the attention and to generate new models capable of surmounting them.

Such hierarchical nature of behaviour is taken into account in the models of the type of hierarchical parallel state machines with a management of bidirectional exchanges between levels (downward control followed by ascending information feedback). The models of type hierarchical ASM and PHISH-Nets also integrate hierarchical structuring, but with an ascending mechanism of communication only that allows the superior level to choose among the actions proposed at the lower level.

3.1 Attentional mechanisms for action selection

Shallice [60] has proposed two kinds of attentional mechanisms for the selection of actions: the *Supervisory Attentional System* and the *Contention Scheduling System*. The *Contention Scheduling System* is used to select in an automatic manner actions to be carried out when a situation is routine. The typical example is car driving: when past the learning phase, a driver can change speed and orientation, while talking with passengers, carrying out a phone call, or listening to the radio. To be able to do that, action selection has to occur automatically, as an important part of conscious cognitive load is used for speech information processing.

The driver can shift gear, which implies a simultaneous manipulation of the clutch pedal and the control lever, while conversing with the other passengers, listening to the radio or thinking of scheduling the activities of the week-end. When confronted with a new situation or when parameters of a situation enforce a change of habit, the *Contention Scheduling* cannot intervene any more, because it cannot select the adequate actions itself. In that case, it is the *Supervisory Attentional System* which forces choices triggered by *Contention Scheduling*. The *Supervisory Attentional System* is a system with limited capacity, used for a variety of intentions, including:

- Tasks involving planning and decision-making;
- Situations in which the automatic reaction process appears to get in trouble;
- New situations;
- Technically difficult or dangerous situations.

The EGO autonomous control architecture for long-term human-robot interaction of the Sony QRIO robot is a recent example of a hierarchically organised control architecture with an action selection algorithm motivated by the contention scheduling model [15]. Out of all the models presented in the previous section, only HPTS++ can manage this coordination of several threads of activity in an automatic way, thanks to its management of physical resources.

3.2 Mechanisms of activation and inhibition

The brain is a simulator of action, a generator of hypotheses. Anticipation and prediction of consequences of actions based on the memory of past ones is one of its fundamental capabilities [39]. There is neither any mechanism of perception apart from action, nor any mechanism of attention apart from action selection[48]. To decide is not only to choose between several solutions, it consists also of blocking undesired behaviours, i.e. *inhibiting* [6]. Processing of tasks is protected from interruptions, particularly for complex tasks (e.g., [38, 28]). Inhibiting mechanisms are very important as they prevent unnecessary elements to enter working memory[5]. A mechanism of *will* is used to avoid any interruption of an ongoing behaviour through a direct inhibition of all competitive behaviours [41, 9]. R. Lord and P. Levy [41] suggest that several complementary rules are at work:

Proposition 1: the instantiation of a goal is going to privilege the closest information in terms of category:

- (a) by increasing the speed with which this information can be reached;
- (b) by increasing the importance to access such information.

Proposition 2: the activation of a goal is going to prevent the instantiation of competitor goals:

- (a) by increasing the latency of their activation;

[5] Active memory dealing with both the treatment and preservation of requested short term information.

- (b) by reducing the priority to access such information;
- (c) by producing negative primary effects.

Proposition 3: the normal realization of an intention deactivates the referring structures, by releasing the cognitive system of the positive and negative affects.

Proposition 4: the repeated failure of a goal can deactivate the referring structures, by releasing the cognitive system of the positive and negative affects.

Proposition 5: the automatic follow-up and detection of conflicts is an important bottom-up control mechanism which integrates biological needs and processes at the symbolic level.

Deliberation implies the existence of at least two candidate solutions. The brain has to make a clear choice between competing solutions. A. Berthoz [6] postulates that a double mechanism of modularity and hierarchy is used:

- Modularity, because the basal ganglia of the thalamocortical base are specialized in the control of the movements of glancing, gesturing, or uses of memory;
- Hierarchy, because it is possible that these parallel modules have a hierarchical cross-wise connection.

A. Berthoz [6] presents three kinds of architectures that have been proposed in the literature for action selection:

1. Subsumption: actions endowed with a hierarchical index, allowing to select them automatically with respect to a fixed order.

2. Organization of actions in a network: mutual inhibitive connections between all actions in a distributed action network that is connected to sensors and effectors.

3. Supervisor or central selector: it activates the circuits selectively. This approach allows to drastically reduce the number of connections and offers at the same time more flexibility. It combines the advantages of modularity and centralism.

A link can be made between the first approach and the behaviour rules and finite automaton approaches presented in section 2.1. The second approach can be mapped to the sensor-actuator approach also presented in section 2.1 and by the competitive action selection mechanisms presented in section 2.3. HPTS++, presented in section 2.3, is a representative of the third approach. The tradeoffs of the different design approaches have been studied in a range of instantiated cognitive control architectures, in particular in cognitive robotics [30, 13] .

3.3 Activity Theory

For W.J. Clancey [17], activity theory (as developed by Lev Semyonovich Vygotsky and furthered Alexei Nikolaevich Leontjev) is a precursory form of situated cognition that will be presented in the next paragraph. The three levels distinguished by activity theory are:

- the activity (motivations): forces operating on the decision taking process;

- the action (goals): what should be done;
- the operations (conditions): how it should be done.

Building upon these premises, M. Sierhuis defines activity in his doctoral dissertation [61] as follows:

An activity is a collection of actions performed by one individual, socially constructed, situated in the physical world, taking time, effort, and application of knowledge. An activity has a well-defined beginning and end, but can be interrupted.

It is proposed that to understand the notion of activity, it is necessary to take into account the fundamentally social nature of human activities. Our activities as human beings are always forged, forced and made significant by our continuing interactions with the worlds of work, the family, and the other communities to which we belong. An activity thus is not only something we do, but a way of interacting. Any human activity is deliberated, but a purpose is not necessarily a problem that must be resolved, and not every action must be necessarily motivated by a task to be carried out. W.J. Clancey [16] takes the example of a person who listens to music while driving their car on their way back home: This activity is a part of the driving practice for many persons, but is in no way a necessary sub-goal to reach their destination.

According to Clancey, the motives underlying human behaviour are imperfectly characterized through the problem solving theory introduced by Allan Newell in his unified theory of cognition [49]. Not all goal oriented behaviours are obtained by inference or compilation. Certain actions simply reproduce cultural motives, whereas some others are coordinated without deliberation by using mechanisms of attention and adaptation. Clancey discusses the notion of parallelism of tasks. A person does not perform multitasking in parallel, rather, several tasks take place simultaneously by merging attentively several parallel interests. Clancey states that the conceptualization of this notion is still primitive and that its nature is underdeveloped in neuropsychological theories. This direction is being furthered in a recent thrust of research into non-classical views on human behaviour (e.g., [48]).

In [7] A. Berthoz and J.L. Petit assert the existence of at least five closed loops of neuronal circuits (basal thalamus-cortex-ganglions) which work in an autonomous way and in parallel, thereby allowing to control the movements of eyes, limbs, memory, and feelings: these closed loop systems coordinate in a dynamic way. Contrary to the problem solving approach, Clancey defends that an activity is not necessarily interrupted when another need arises, as, for example, when another activity becomes pressing or if an external condition comes to interrupt what the person was doing. This would imply a mechanism of competitive activation. The starting and ending of an activity are more subtle than a purely goal oriented decision. Clancey states that there is no opposition between notions of sequencing and parallelism, but rather a coupling of them. These coupled sub-systems need to be organised in real time. Parallelism allows to organise several activities at the same time, whereas serialism forces the processing of ordered forms of sequences of action. Parallelism is fundamental to couple behaviours and to temporally order them, in particular when they regard several sensori-motor modalities.

Out of all behavioural models, hierarchical parallel state-machines allow this combination of the sequential and parallel aspects. Out of these models, HPTS++ in particular appears to be able to take into account the various sensori-motor modalities and the activation/inhibition principles in a generic way. The Behavior-Oriented Design approach discussed [14] provides a principled analysis of behaviour-based designs and tradeoffs regarding this particular perspective.

3.4 Embodied and Situated Cognition

Representation is the central notion of traditional cognitive science to the detriment of the physical and environmental context in which cognitive systems are brought to operate. It is common to consider that only the symbolic approach can be used to model cognitive behaviours, because these were often conceived as problems to be solved in the form of condition-action rules. However, this traditional approach of cognitive science and artificial intelligence has been confronted with challenges such as the Chinese room [59]: the fact of disposing of symbols and rules allowing to manipulate them does not yet define any kind of intelligence, because at no time there is usage of their meaning.

In reaction to such criticism, the notions of situatedness and embodiment gained in importance in cognitive science at the end of 1980s [75]. In this perspective, cognition is not reduced to an intellectual demonstration any more, but it also and importantly involves the body and the physical (and social) environment(s). The body of the agent as well as the environment in which it operates induce structures which the internal cognitive devices of the cognitive agent can and need to use to solve the agent's problems [3, 37].

Intelligence can then be described as the sum of the previous physical experiences of the agent acquired through its interaction with its environment. In other words, the intelligence of an agent is based on its previous interactions with the physical world. Brooks [12] introduced the hypothesis of the importance of physical grounding which postulates that the intelligence of an agent must be based on the interaction between the physical agent and its environment. According to Harnad [29], symbols have to acquire their common sense, it is what he calls the symbol grounding problem:

an artificial system based completely on the manipulation of symbols never glimpses semantics which is associated with them.

To find a solution to this problem, he proposes that symbols be based on a process of invariance extraction from sensori-motor signals, defined in three stages:

Iconisation: the processing of the signals into iconic representations or icons;

Discrimination: the capacity to judge whether two inputs are identical or different and if they are different, in what way they differ;

Identification: the capacity to assign a unique answer to a class of inputs, treating them quite as equivalents of a certain way.

While there is a consensus in the situated and embodied cognition community in critiquing the traditional approach to cognition as computational process as incomplete or even erroneous, there is, on the other hand, no clear consensus on the definition of the foundations of the new approach, as reflected in the recent proposals of interactionism or enactivism (e.g. [8, 69, 1, 62]).

3.5 Ecological Theory

W. Warren [72] stated that *the goal of perception is not to provide the general description of a scene but to extract specific information for the task implied in the activity in progress.* and thereby joined J. Gibson [27] who proposed an ecological approach to perception, a theory which associates a behaviour-based semantics with each object of the environment. Gibson developed a theory of the affordances, a term that is not easily to translate, but which essentially corresponds to the perceptible physical availabilities and invitations of an object, place, or situation. The stress is laid not on the nature of observed but on the nature of the observer who wants to access immediately the characteristics of the object or the environment which interests them.

Thus, an environment will provide directly to the behavioural entity all of the possible behaviours with respect to the objects and entities which constitute it. Gibson defines a typology of affordances: media, substances, surfaces and their provision, objects, other people and animals, places. This theory postulates that it is more useful to know in advance the nature of the interactions with an object than to have precise concepts of its geometry and to attempt recover its characteristics from that information.

The affordances introduced by Gibson are opportunities for action that an object, a place or an event provide for the cognitive agent. They refer to the resources encountered by the cognitive agent in its environment. This concept of affordance is not dissociable of that of capacity or aptitude (or as yet others say, effectivity). For example, the affordance of a chair is related to our capacity to fold the basin and the knees to be seated. The aptitude is a means of acting that a cognitive agent can use to carry out a particular affordance. The perception of affordances was demonstrated to be dependent on the body of the observer and the latter is a variable notion because depend on whether or not tools are being used (e.g., the cane of a blind man transforms the range of affordances). According to Hirose, the borders of the body are dissociated by the processes of perception and of action and so the use of a tool modifies the perception-action loop [31].

Before use, the tool is an independent object, separated from the body of the cognitive agent. It has specific affordances and gets opportunities of action. During use, a tool is not an object any more; it acts as a functional extension of the agent. It plays a central role by extending or transforming the aptitudes of the agent to identify and carry out affordances in its environment. When a tool extends the capacities of an agent, it also extends its body.

In this context, the development of a fruitful dialogue between philosophy, cognitive science, and artificial intelligence and engineering can be remarked, that set out with the development of architectures such as PENGI [2] and Polly [32] and related developments as also covered in the first main section of this paper. Publications such as [24] are a clear indication for how mutual awareness and engagement across the camps has been established, and document how engineering has been able to return contributions to theoretical analysis.

4 Conclusion

The main finding regarding the investigation on existing links between reactive action selection models in animation and work in cognitive science on action selection mechanisms is that there are still ample opportunities for improved collaboration (cf. e.g., [63]). There are only few discussions in the behavioural animation literature or in artificial intelligence about the cognitivist foundations of the proposed models, apart from the recent field of the embodied and situated cognition. This last research field is really multidisciplinary and is gathering researchers from cognitive science, cognitive robotics and artificial intelligence. Finally, within the reactive models proposed in computer science HPTS++ appears to stand out as one of the few models integrating most of the presented notions.

However, decision making is not self-sufficient and should be integrated in a multilayered behavioural architecture. Usually, such architectures are based on rule-based systems and refer to classical disembodied and unsituated cognitivism. Clancey criticises that deliberation is not a kind of time-out for action. Deliberation in fact occurs as a sensori-motor experience and does not take place before or between perception and the action. Deliberation is not a higher level process in the sense of control but in the sense (direction) of the organization of the way we perceive (collect), order, or give meaning to material and experiences (experiments) already created.

New cognitive architectures are being developed that take the perspectives of interaction, embodiment and situation, and enactivism into account, e.g. in EC-funded artificial cognitive systems research, with the umbrella coordination actions euCognition and euCog II[6] (see e.g. [69]). One of the most challenging problems remains the management and coordination of bottom-up and top-down, exogeneous and endogenous influences in unified architectural designs.

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