An Interdisciplinary Research Approach to Political Science – Specific Modeling and Simulation Tools

Voinea, Camelia

AN INTERDISCIPLINARY RESEARCH APPROACH TO POLITICAL SCIENCE – SPECIFIC MODELING AND SIMULATION TOOLS

CAMELIA VOINEA

This paper introduces a research approach on new modeling and simulation techniques for the social and political behavior and attitude in the context of social and political change. Political Science needs specific analysis, representation, modeling, simulation and predictive tools. The need for such techniques is motivated by the increasing complexity of the empirical experimental data and conceptual knowledge involved in the representation, analysis, modeling and prediction of social behavior and attitude with respect to social and political value systems, especially when such values are subject to social change processes. The work reported here aims at developing a more believable approach on artificial agents and artificial societies by means of: (i) new representation and modeling concepts of the artificial agent as an agent-environment interaction system, (ii) new representation and modeling concepts of the interaction and knowledge in artificial agents, and (iii) new computational theory explaining the learning and the emergence mechanisms of social behavior and attitude in an artificial society. The concepts of autonomous agents, agent-environment interaction systems (aeiss), and computational attitude are defined and explained. Attitude emergence in artificial society is defined and explained by means of the Theory of Learning. A Case Study on attitude emergence in the simulation of a team cooperation game is described, analyzed and an interpretation of the computational attitude is provided.

Keywords: behavior learning, attitude emergence simulation, artificial autonomous agents, artificial society.

1. Why Study Attitudes?

This paper introduces a research approach on new modeling and simulation techniques for the social and political behavior and attitude in the context of social and political change.

The need for such techniques is motivated by the increasing complexity of the empirical experimental data and conceptual knowledge involved in the representation, analysis, modeling and prediction of social behavior and attitude with respect to social and political value systems, especially when such values are subject to social change processes. The degree of complexity of such data and knowledge regards not only the collection of data, but mainly the representation and processing of such huge amounts of information in order to reach valid predictive outcomes. In this respect there are several specific approaches provided by the so-called Sciences of the Artificial, namely *Artificial Intelligence*, *Machine Learning*, *Artificial Life*, *Autonomous Agents*, *Artificial Biologically-inspired Evolving Systems, Immunotronics,* to name just a few. Much of the research approaches elaborated in these scientific and information technology areas are essentially aimed at providing *an artificial society system* as a means of analysis, representation, modeling and simulation of the real society in the artificial: the *agents* as a representation of the human actors, the *society of agents* as a representation of the real human society, the social relations, the society evolution model etc. This kind of artificial society is usually represented as a *MultiAgent System* (MAS), as a *Distributed Artificial Intelligent System* (DAI), *Software Agent System* (SA), *Artificial Neural Networks* (ANN), *Cellular Automata* (CA) and many others. The unifying "thread" of all such research approaches is their interdisciplinary character combining computational, cognitive and normative social models which might enable any type of artificial agent (either embodied or virtual) to develop believable social behavior and to (self)organise in groups and societies. These researches provide the means to fight a major drawback of the classical empirical research, Statistics or Game Theory which put too much emphasis on logic, rationality and economic principles and too little on the cognitive and normative aspects. From this point of view, the work reported here aims at developing a more believable approach to artificial agents and artificial societies by means of: (i) new representation and modeling concepts of the artificial agent as an agent-environment interaction system, (ii) new representation and modeling concepts of the interaction and knowledge in artificial agents, and (iii) new computational theory explaining the learning and the emergence mechanisms of social behavior and attitude in an artificial society and its predictive power.

This approach aims at providing an Artificial Life-based simulation tool for studies and researches on political science issues like the voting behavior, the political attitude, the political leadership, the political organization and decision-making.

In order to elaborate such a simulation tool we proceed by defining proper concepts and principles concerning the type of social actor we model as an artificial agent, the appropriate concepts and principles of computationally representation of such agents and multiagent systems, and the appropriate computational theory concerning the emergence of attitudes in such artificial social systems.

There is already much research work on such interdisciplinary issues. The most investigated areas are almost always those which involve human beliefs, intentional behavior or just society, because these areas allow the young sciences of the artificial to reach and conquer a "promised land" – a land of knowledge and research on human brain, mind, and cognition. To select only one of these most appealing issues, let us take a look on the scientific literature on the social attitude.

The domain of attitudinal theory and research is quite huge. The interest in this topic is widespread because of the evidence that much of our personal and social life and behavior is influenced by psychological attitudes. A psychological attitude is something hard to define since it involves a huge diversity of other complex concepts and representations of human thought, cognition, reasoning and affect, like: *beliefs, desires, feelings, hopes, judgments, opinions, emotions, and wishes*, to name but a few. It seems that our experience is inevitably related to one or another of these phenomena. Another reason for the interest in attitudes comes from another evidence, namely that our behavior is influenced by our attitudes, whereby the attitude is seen as the "cause", while behavior is seen as the "effect"[1]. In this regard, psychological attitudes become very important for the study of *why* and *how* behaviors and attitudes are related to each other.

A huge amount of research work has been developed in the study of attitudes both in social psychology and in cognitive sciences. My previous work[2] on computational analysis, representation, modeling and simulation of attitudes and its applicability in the learning theory has found insight in the American school of social psychology represented by the works of Gordon W. Allport[3], W. Doob[4], W.J. McGuire[5] and D.W. Rajecki[6].

This paper is organized as follows: in ***Section 2*** an overview on the scientific literature concerning the attitude modeling is provided. ***Section 3*** describes the shifts in modeling paradigms induced by interdisciplinary researches on human intelligence, memory and knowledge and introduces the new concepts and modeling principles which proved to be more appropriate for social and political modeling and simulation of attitude in the artificial. ***Section 4*** defines the concept of the *Agent-Environment Interaction System* and the foundation of a proper attitude emergence simulation paradigm: *learning_while_interacting*. ***Section 5*** is a follow-up of this paradigm specification: it provides the conceptual definition of a *computational attitude* and of an artificial society simulation architecture which provides for believable behavioral organization and development.

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1 F.C. BARTLETT, *Remembering*, Cambridge University Press, 1932.

2 C.F. VOINEA, *Learning from Change. Foundations of a Theory of Learning in Agent-Environment Interaction Systems*, Doctoral Dissertation, 1997.

3 G.W. ALLPORT, "Attitudes", in C.A. Murchinson (ed.), *A Handbook of Social Psychology*, 2, Russell & Russell, New York, 1935.

4 L.W. DOOB, "The Behavior of Attitudes", in *Psychological Review*, 54, 1947.

5 W.J. McGUIRE, "The nature of attitudes and attitude change", in G. Lindzey, E. Aronson (eds.), *The Handbook of social psychology*, 2nd edition, 3, Reading, Addison-Wesley, 1969.

6 D.W. RAJECKI, *Attitudes: Themes and Advances*, Sinauer Associates Inc., Sunderland, MA, 1982.

Section 6 is a presentation of the *Theory of Attitudes* and its representation, modeling and predictive characteristics and power. ***Section 7*** resumes the case studies and the simulations of attitude emergence scenarios which provided the means for a comprehensive performance analysis and evaluation. In Section 8 some conclusions are drawn and future work guidelines are generally described.

2. Modeling Attitudes: What is an Attitude?

2.1. *The Attitude in Social Psychology Research*

As Allport defines it, the *attitude* is mainly concerned with our experience and the dynamic organization of our behavior depending on our attitudinal experience. He defines the attitude as a

> ... mental or neural state of readiness, organized through experience, exerting a directive or dynamic influence upon the individual's response to all objects and situations with which it is related.

In a rather dynamically evolving view meant to emphasize the fundamental relation between attitudes and behaviors, Doob has defined the attitude mainly from the point of view of the influence it has on behaviors' co-ordination. In his approach, an attitude is defined as

> ... an implicit response, which is both anticipatory and mediating in reference to patterns of overt responses, evoked by a veriety of stimulus patterns as a result of previous learning or gradients of generalization and discrimination, itself a cue and drive-producing, and considered socially significant in the individual society.

According to this view, the attitude can be best defined by means of three basic components: (A) Affect – the evaluative component, (B) Behavior – the intentional component, and (C) Cognition – a component which concerns beliefs about the attitudinal object. As attitudes are viewed as a source of behavioral motivation and organization, the best way to understand how attitudes relate to our behavior is to describe their fundamental functions. McGuire has summarized four reasons why attitudes exist at all: (i) the utilitarian or adaptive function, (ii) the economy or knowledge function, (iii) the expressive or self-realizing function, and (iv) the preserving or ego-defensive function.

This approach on modeling and computational representation of attitudes focuses on those aspects and components of attitudes which provide for an explanation of the way they dynamically influence behavior and learning: (A) affect, (B) behavior and (C) cognition.

2.2. *The Attitude in Cognitive Psychology Research*

The cognitive psychology approach on attitudes studies mainly the affect component. Much of the research work in this area focuses on the attentional processes, which influence the agent's goal-achieving behaviors. The attitude is therefore viewed as basically determined by the emotions the agents might experience with respect to their own goals. In this view, the attitudes are defined as "valenced reactions to events, other agents, and objects"[7] based on affect and emotional cognitive structure which influence the attentional power of the agents in pursuing their goals.

This orientation of cognitive research has mainly developed towards comprehensive computational models of communication and affective human-machine dialog, in which some of the relationships between communication and affect are explored[8]. Such computational models need system architectures that make various kinds of affective states possible in the artificial intelligent agents, along with some implications for the various communication processes. The basic assumptions for this kind of modeling include the idea that human beings have typically many different, hierarchically organized *affective dispositions* capable of interacting with new information to produce affective states, distract attention, and interrupt ongoing processes, providing for a tendency to penetrate an attention filter mechanism which seems to account for the partial loss of control involved in emotions. The role of affect in the cognitive development of autonomous agents turned into research on phenomena commonly referred to as *emotional* (*affective states*). In this respect, agents' behaviors are considered as the results of the interactions of two architecture subsystems: a physiologically-based, low cognitive-complexity motivational system – on the one hand – and a conceptual representation-based, high cognitive-complexity goal processing system – on the other hand. An artificial autonomous agent has to adapt to changes in its world in order to ensure its continuing survival. Autonomous agent's behavior is viewed as based on an "existing motivational system that guides its behavior and influences its on-going cognitive development"[9].

Research work on learning in autonomous agents has focused mainly on the role of affect and emotions in the perception and attentional processes that guide behavior. Learning allows people to adapt to an ever-changing environment and to develop new forms of behavior in order to achieve the many

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[7] A. ORTONY, G.L. CLORE, A. COLLINS, *The Cognitive Structure of Emotions*, Cambridge University Press, 1988.

[8] A. SLOMAN, "Prolegomena to a Theory of Communication and Affect", in A. Ortony, J. Slack, O. Stock (eds.), *Communication from an Artificial Intelligence Perspective: Theoretical and Applied Issues*, Heidelberg, 1993, pp. 229-260.

[9] T. READ, *The Role of Affect in Cognitive Development*, Birmingham School of Psychology, Technical Report, 1992.

goals that they have at any one time. This learning is mediated by various attentional processes and focused on what the agent considers to be important for achieving its current goals.

2.3. *The Attitude in Researches on Memory, Remembering and Learning*

The early work of Bartlett[10] regarding the re-constructive memory and processes of recall and the more recent work of Walter Freeman[11] on the neuropsychology of learning, emotional and social behavior processes are providing a fundamental assumption for a computational theory on attitude learning: both authors are trying to define attitude as a dynamic process fundamentally based on the capacity of re-constructive recall of the human memory. There are no fundamental differences between their models of attitude. If there is any such difference, then this could reside on different scientific perspectives over the human memory: in the case of Bartlett we deal with a psychological perspective over remembering processes, while in the case of Freeman we deal with a perspective based on the cell neurophysiology and biochemistry. Though their research approaches are elaborated in time at a distance of more than 60 years, there is a common thread unifying their thinking. This common thread rather concerns the concepts of information, memory and recall than concepts regarding the psychological roots of social behavior. But more on this in the coming up sections.

What is to be emphasized in their researches is that the attitude names a complex *psychological state or process* which builds up dynamic representations of the past experience. As Bartlett puts it, these dynamic representations of some individual past experience are built up as remembering processes in which the recall is a "construction made largely on the basis of this attitude, and its general effect is that of a justification of the attitude".

In this kind of view, an act of *remembering* is not a *retrieval of stored information*, as we usually think when we deal with computational theories on memory and concepts representations. As Walter Freeman says, it is the

> construction of a pattern when an appropriate stimulus or preceding pattern constrains the limbic system into one of its learned basins of attraction, thereby releasing a creative dynamic process for which the outcome is never precisely the same twice.

The point in this view is that it allows for an essential shift in the computational thinking: a shift toward self-organisation in viewing both memory processes and behavioral and attitudinal processes. The issue of

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[10] F.C. BARTLETT, *op. cit.*
[11] W.J. FREEMAN, *Societies of Brains*, LEA, 1995.

re-constructive memory becomes fundamental for a computational theory on attitude emergence and learning and it will be introduced in the next sections.

3. Shift in Research Paradigms: A Point of View on Knowledge, Interaction and Memory

A conventional characterization of an autonomous agent is that of a "machinery" which extracts information about the world by its various sensors and uses this information to construct internal models of its world able to support a decision-making process which identifies further actions to take in order to achieve some goal. This is the classical Artificial Intelligence's (AI) and Machine Learning's (ML) point of view concerning artificial agents as information processing systems. The basic idea is that the world of the artificial intelligent agent can be characterized as a world of "information" and the interaction of this agent with the world can be understood as acquisition and processing of the acquired information in order to produce knowledge about the world and knowledge about how to do something in the world.

The information processing point of view as it has been described by Newell and Simon[12] represents the fundamental paradigm that has shaped our comprehension of the intelligence and learning in the artificial. Classical AI's main rival in the past decade – Connectionism[13] – rejects the idea of explicit symbolic processing as the basic principle in generating intelligent behavior. Nevertheless, it still embodies the concept of information processing applied not at the level of explicit symbols, but at the level of collective behavior of a large number of simple neural computational elements.

In spite of its widespread use, the concepts of *information* and *information processing system* have been seriously weakened by fundamental research works in cellular biology[14], in neurobiology and neuropsychology[15], chemistry and the chaos theory[16], and philosophy[17-18], which have started to be echoed by most

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[12] A. NEWELL, H.A. SIMON, *Human Problem Solving*, Prentice-Hall Inc., Englewood Cliffs, NJ, 1972.

[13] D.E. RUMELHART, J.L. McCLELLAND, *Parallel Distributed Processes*, MIT Press, Bradford Book, 1986.

[14] H.R. MATURANA, F. VARELA, *Autopoiesis and Cognition*, Reidel, 1980.

[15] W.J. FREEMAN, "Chaos in the CNS: Theory and Practice", in R.J. Greenspan, C.P. Kyriacou (eds.), *Flexibility and Constraints in Behavioral Systems*, John Wiley & Sons Ltd., 1994; "Chaos in the Brain: Possible Roles in Biological Intelligence", in *International Journal of Intelligent Systems*, 10, 1995, pp. 71-88.

[16] I. PROGOGINE, I. STENGERS, *Order Out of Chaos*, Flamingo, Harper Collins Publishers, 1985.

[17] M. MERLEAU-PONTY, *Le philosophe et la sociologie. Eloge de la Philosophie*, Gallimard, Paris, 1960.

[18] M. HEIDEGGER, *Being and Time*, Basic Blaackwell, Oxford, 1962.

recent researches in AI, Alife and ML sciences. These researches offered further evidence that biological systems posses the powerful self-organisation mechanisms required to develop and maintain the “dynamical structural couplings that must exist between them and the environment they interact in”[19].

This reality leads to the necessity of re-considering the conception and design of artificial autonomous systems and the type of prediction and simulation applications they can be used to perform. This is what we can describe as the fundamental question for the agent-based simulation architecture design. Situated autonomous multi-agent systems technology is in search for a paradigm that can give the appropriate support to the development of more flexible mechanisms to provide for intelligent behavior in the artificial. What an artificial autonomous agent or multiagent system needs is a proper internal structure and proper internal mechanisms which endow it with the capability of an adaptive behavior within a continuously-changing environment. It is only this kind of internal structure which allows for the development of modeling and simulations applications in the artificial which might mimic in a believable way the real social behavior of the human individuals and provide insight on how artificial society–based prediction might look like in areas like political science, security, cultural transfer, and other issues of societal interest.

Two fundamental issues are being revised in particular: the knowledge level descriptors of behavior and the mechanisms which coordinate perception and action. There are three fundamental hypotheses about cognition which essentially distinguish situated cognition from classical AI and they regard *knowledge*, *memory* and *interaction*.

3.1. *On Knowledge*

It becomes more and more obvious within the research community the trend which regards classical knowledge level descriptors – prototype hierarchies, scripts or strategies – as an observer’s model of behavioral patterns and not as dynamically evolving structures and mechanisms inside the artificial intelligent agent.

What we do know is that knowledge can be represented, but the idea we have about its representation in an artificial multi-agent system is far from the physiological and biological reality of the representation mechanisms in intelligent living creatures. We do not know yet the very mechanism of intelligence in the living, however, as Freeman puts it, there is neurobiological and neurophysiologic evidence which leads us to think that knowledge does have a representation, but this representation cannot be of the type of storage structures like statements of belief,

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[19] F.J. VARELA, “The Re-Enchantment of the Concrete”, in L. Steels, R. Brooks (eds.), *Artificial Life Route to Artificial Intelligence*, LEA, 1995.

scripts or schema of behavior. The point in the representation mechanism resides in the fact that *knowledge* should be viewed as a product of the interaction of the agent with its environment, and not as a physical substrate from which behavior is generated. As a product of the interaction between the agent and the agent's environment, it cannot be reduced to – or replaced by – representations of behavior or of the environment: knowledge is a product of agent-environment interaction mechanisms and is subject to agent's interpretation over repeated cycles of perceiving and acting. Knowledge arises as a side-effect of this interaction and it exists as such as far as the interaction exists and the agent finds its meaning by associating it to a particular kind of contextual (environmental) change.

3.2. *On Memory*

It is common place already the notion of "memory structures" which hold knowledge and provide it whenever recalled by means of retrieval procedures. Whatever these "memory structures" look like, they are assumed to be "meaningful structures" both from a formal and from their content point of view. The point situated cognition makes on memory is that such "meaningful structures" are not fixed, given or static in either the environment or in human memory[20]. The memory of the living creatures in not a place where things like schema, category, rule, procedure, script or frame are stored. Knowledge is *not stored* as it is in the computer systems, but *constructed* each time innate or acquired "meaningful structures" are used[21]. Therefore, memory should be thought of as an interaction and pattern re-construction rather than a storage device. This approach would make a significant difference between the classical agent (multi-agent system) as an information processing system and the artificial intelligent agent (multi-agent system) as an artificial autonomous system: this difference should be expected to influence the knowledge representation and the interaction with the environment.

3.3. *On Interaction*

The classical computational systems address the information processing problem of identifying and classifying properties of the world. The problem the autonomous agent (multi-agent system) faces is that of guiding their actions in the environment on the basis of perceived information in some local context. Since such situation would permanently change as a result of the intrinsic dynamics of the environment and also as a result of the agent's (multi-agent system) actions, the

[20] W.J. FREEMAN, "Neural Networks and Chaos", in *Journal of Theoretical Biology*, 171, 1994, pp. 13-18.

[21] F.C. BARTLETT, *op. cit.*

reference system for understanding the perceived information is no longer a pre-determined perceiver-independent world. It is the agent's (multi-agent system) embodied structure which provides the physical support of its cognitive functions. This point of view has been called the *enactive* approach[22] to perceptually guided action: its overall concern is not to determine how some perceiver-independent world is to be computationally recovered, but rather to determine the principles which explain how action can be perceptually guided in a perceiver-dependent world. The enactive approach captures an essential feature of what an artificial autonomous agent (multi-agent system) should be: it views the agent and its environment as structurally coupled[23]. The notion of structural coupling will be adopted in the computational attitude theory as well.

4. The Agent-Environment Interaction Systems

The *Agent-Environment Interaction System* (*aeis*) is viewed here as a dynamical system. Our basic assumption for the understanding of the autonomy of artificial agents (multi-agent systems) is that autonomy emerges from the learned attitudes as a means of self-control over co-ordinated behaviors, where by "behavior" we mean both innate and learned behavior.

The traditional view upon artificial intelligent agents (multi-agent systems) is that of systems which *act* on the environment so as to change the state of the environment in some way and to keep track of this change in such a way that the return the agent gets from the environment reinforces its actions until a goal is successfully accomplished and the respective return is maximized.

This information processing view has a fundamental weakness in that it establishes some kind of sequential "sense-think-then-act" cycle[24], hence committing the agent to become a "medium" in which "sensed information" is transformed into "representations" of situation-action pairs (from which it can then select the most rewarding ones) and to transform back this representation into information which guides the performing of the selected action.

What an agent does in reality is not to act on the world as something separate from the world. The agent is part of its environment and its actions are due to being a part of this environment. The agent does not simply act, but interact with the world. Both the agent and the environment are shaped by this interaction. It is the dynamics of this interaction that we are interested in and also in the way the agent acquires autonomy in its own environment.

We can therefore proceed to the conceptual specification of the artificial autonomous agent (or multiagent system) as a system of dynamically

[22] F.J. VARELA, *The Embodied Mind*, MIT Press, 1992.
[23] *Ibidem*.
[24] A. NEWELL, "The Knowledge Level", in *Artificial Intelligence*, 8, 1982.

interacting processes: these processes belong to either the agent or the environment, and the effect of their interaction is quantified in both the agent and the environment.

Let us think of these two interacting entities – the *Agent* and the *Environment* – as a whole, as a system in itself: the *agent-environment interaction system*. Let us further consider $\boldsymbol{S}$ to be the *state space* (where by "state" we mean both agent's specific states and environmental specific states), and $\boldsymbol{W}$ to be the interaction *state* space (where by "interaction state" we mean states dynamically emerging from the interaction between the agent and its environment and directly quantifiable in both the agent and the environment). Thus we can define a mapping from pairs of *specific states* to *interaction states* such that an *interaction functional operator* ($\boldsymbol{I}$) transforms a pair of arbitrary specific agent's ($\boldsymbol{s_a}$) and environment's ($\boldsymbol{s_e}$) states into an emerging *aeis' state (*$\boldsymbol{s_{aeis}}$*)*:

$$\begin{aligned} &\boldsymbol{I : S \times S \rightarrow W,} \\ &\boldsymbol{I(s_a, s_e) \mapsto s_{aeis}} \quad \mathit{for} \quad \forall \boldsymbol{s_a, s_e} \in \boldsymbol{S}, \forall \boldsymbol{s_{aeis}} \in \boldsymbol{W, S \subset W} \end{aligned} \tag{1}$$

In other words, any interaction will extend the initial state of specific states ($\boldsymbol{S}$) with emerging new states ($\boldsymbol{s_{aeis}}$) such that the *aeis* state space ($\boldsymbol{W}$) will grow each time and as long as the agent and the environment interact with each other.

Let us now consider $\boldsymbol{P_i}$ and $\boldsymbol{P_j}$ two *dynamically correlated processes* such that $\boldsymbol{P_i}$ transforms an agent state into an environmental state, and $\boldsymbol{P_j}$ transforms an environmental state into an agent specific state:

$$\begin{cases} \boldsymbol{P_i(s_a) = s_e} \\ \boldsymbol{P_j(s_e) = s_a} \end{cases} \tag{2}$$

We say that $\boldsymbol{P_i}$ and $\boldsymbol{P_j}$ are *dynamically correlated* if their effects (either independently or cumulatively) can be quantified and represented as a new emerging state of the *agent-environment interaction system*:

$$\boldsymbol{I(s_a, s_e) = I(P_i(s_e), P_j(s_a)) = s_{aeis}} \tag{3}$$

Simple examples of such processes are the processes of environmental change like variations of temperature which usually produce variations of the agent internal state (*homeostasis*). Another example concerns the processes of change of the level or intensity of social regard which may produce corresponding variations of the agent psychological state for agents which are sensitive to social relations gradients.

Define a ***behavior*** as a pair of dynamically correlated processes in which each process represents an action resulting in a transition to another state, and a pair of such processes represents an interaction resulting in a transformation of both agent and environment specific states into a new emerging state in their interaction space.

Define an ***agent-environment interaction system*** as a dynamic system of interaction processes.

Define an ***autonomous agent*** as an agent-environment interaction system of coordinated behaviors.

Define a ***computational attitude*** as a behavioral capacity of an autonomous agent to adapt to a social environmental change or stimulus.

5. The Computational Attitude

Computational Attitudes are representations of the overall behavior of an artificial autonomous agent (multi-agent) system defined as an *aeis*. It serves as the fundamental mechanism of the *aeis* behavioral emergence patterns in dynamically changing social contexts.

The attitudes of the artificial autonomous agent with respect to the environmental contextual variations emerge and operate at the level of the cognitive functions which associate *aeis'* behaviors to the control *aeis* is able to perform over its contextual situations. Their fundamental role is to "couple" the *change* in the agent with the *change* in the environment in a controlled manner, where by "control" we mean the control an intentional autonomous agent has over its own goal-achieving and world-cognitive means. We assume that this (self)control is performed by the autonomous agent by means of ***coordinating*** several simultaneously active (innate and acquired) cognitive behaviors.

The ***self control problem*** in an artificial autonomous agent defined as an *aeis* can be stated as follows: given an *aeis* characterized by a $\boldsymbol{n} \times \boldsymbol{m}$-dimensional state space, find a (self)control function of $\boldsymbol{n} \times \boldsymbol{m}$ parameters (if such function exists) which takes as input an $\boldsymbol{m}$-dimensional change in the environment and generates as output an $\boldsymbol{n}$-dimensional behavioral change by transforming the $\boldsymbol{m}$-dimensional environmental change into a self $\boldsymbol{n}$-dimensional agent internal change which follows-up the input as an instantaneous dynamic goal.

In other words, the self control problem of an artificial autonomous agent (multi-agent) system which faces environmental contextual changes is to find a coordination policy which provides for the agent overall behavior in the state space. This coordination policy is called ***computational attitude*** (see Figure 1). The formalism used to define the computational attitude is based on Variational Calculus.

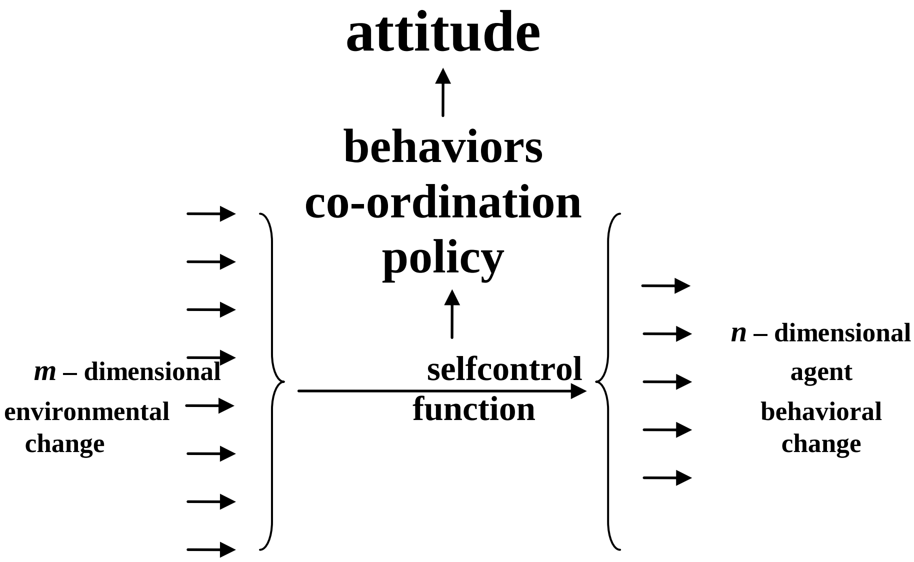

Figure 1. The fundamental role of the computational attitude is the "coupling" of a *m*-dimensional environmental change to a ***n***-dimensional agent behavioral change

The ***computational architecture*** of such a control function over ***n***-dimensional behavior change relies on a *Behavior Coordinator Subsystem* which provides for the coordination policy, and on a *Re-Constructive Memory Subsystem* which provides for dynamic representations of the knowledge from interaction called *Behavioral Couplings (cobs)*.

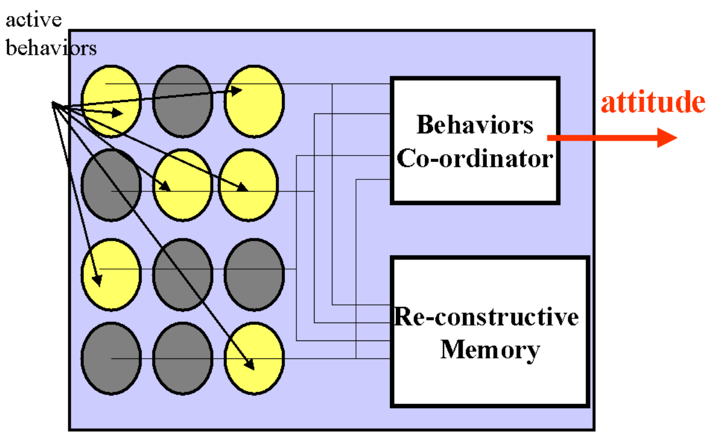

Figure 2. A computational attitude architecture

The Theory of Attitudes relies on a learning paradigm called ***learning_while_interacting*** and proves that the Behavior Coordinator function can be approximated by an Attitude Learning (A_Learning) function[25].

6. The Theory of Attitudes

The ***Theory of Attitudes***[26] is based on the concept of computational attitude in an artificial society of autonomous agents and puts forward the foundations of a general social learning theory in agent-environment interaction systems (***aeis****s*).

The Theory of Attitudes views learning in ***aeis****s* as a fundamental means to dynamically correlate the variation in the interaction space to the structural and cognitive change in the artificial agent's behavioral patterns. It represents the conceptual foundation of a research paradigm on the attitude emergence in an artificial society. This theory is two-folded: one of its pillars is represented by a general view of the artificial *aeis* as an artificial learning system, and the other is a view of the attitude emergence as based on behavior coupling processes.

The learning process structure of an autonomous agent (multi-agent) system defined as an *aeis* consists of the following classes of processes: *(i) interaction processes; (ii) gradient-following processes; (iii) predictive processes; (iv) coupling processes; (v) re-constructive memory processes.*

The Theory of Attitudes proves that agent's ***attitude*** with respect to an environmental change emerges as the ***aeis*** learns successive approximations of behavioral co-ordination function by dynamically associating ***minimal attitude values*** (i.e., corresponding to optimal trajectories in the state space w.r.t. the agent's goal) to ***self-rewarding values*** (internal payoffs) and ***behavioral couplings*** (i.e. dynamic representation of knowledge from interactions). In other words, the computational attitude is a representation of the attitude emergence mechanism. This mechanism computes an agent's attitude with respect to some dynamic (spontaneous) social environmental change by associating various "utility marks" to new knowledge learned or dynamically constructed during the on-going interaction processes.

This approach is similar to other approaches concerning learning based on reinforcement. What distinguishes this approach from the others is a difference in (1) the definition of the autonomous agent as an *aeis* and (2) in the definition of the rewarding signals: while in Reinforcement Learning this rewarding signal is defined outside the agent, in Attitude Learning the internal

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[25] C.F. VOINEA, *op. cit.*
[26] *Ibidem.*

reinforcement is elaborated by the agent itself (self reinforcement) as a means of co-ordination its own behaviors with respect to the current goal.

The Theory of Attitudes is fundamental for the development of a social simulation tool: it allows the design of artificial autonomous agents (multi-agent) systems which can re-produce human social behavior in a computational medium in a believable manner. It is important also for modeling and simulating complex cognitive and normative aspects of the human behavior and society in comparison with the Bayesian Theory, for example, which can account for a belief system, but cannot take into account a dynamically evolving artificial multi-agent system with normative, behavioral morphology and situated cognitive aspects.

7. Applications of the Theory of Attitudes: Modeling Social Multi-Agent Systems

In this paper we have been mainly interested in software autonomous agents who are able to develop collaborative group behaviors and learn a class of norm-oriented behaviors from interactions with their environment. An approach on group behavior might concern at least two alternatives: (i) in the sense of the Game Theory, i.e. based on economic gain principles, or (ii) in the sense of Social Sciences, i.e. based on knowledge representation and learning. The choice of the type of theoretical approach has deep implications at the practical level in designing and experimenting with artificial Multi-Agent Systems.

The previous and current approaches on Multi-Agent Systems (MAS) are based on economic principles of cumulating high payoffs over time using instrumental reinforcement-based techniques, planning and hierarchical cumulative individual contributions to the accomplishment of a group goal. The agents are viewed as separate individual entities, relying on reward deliverance for action decision making. The general outcome of such a MAS architecture is an optimal group behavior with respect to criteria concerning: (i) the state space representation and search; (ii) the goal representation as reward / punishment, and (iii) the action decision making, usually based on planning and distributed action execution. The advantage of this kind of approach is the easy of the mathematical formalism provided by the Game Theory and Dynamic Programming. However, there are also some disadvantages: (i) the need for planning involves a time-consuming type of approach and the use of fixed pre-defined knowledge structures whose real-time management and update represent drawbacks on its performances in the field; (ii) this economic-gain type of MAS is not always “believable” from the point of view of the team behavior, for team behavior is not always a matter of combinatorial optimization of the behavioral contributions of the member agents of a MAS to the accomplishment of a shared goal. There is no group knowledge shared by the member agents, and the aspect of group behavior is often a matter of combining instrumental techniques to make the agents' behavior convergent on the accomplishment of a shared goal.

7.1. *Norm-oriented behavior. Norms Representation*

The concept of *norm* is meant to combine two aspects: (a) the *cognitive* aspect and (b) the *operational* aspect.

From a cognitive point of view, a norm is defined as a *permission* or an *obligation for an agent in an agent society* to do or to not do a certain action in that specific agent society[27].

The *operational* aspect concerns the way this concept should operate in a real-time goal-oriented MAS action execution framework.

In our approach, the notion of norms is directly connected to the notion of a *role* a social agent can play with respect to a norm[28] [29] [30]. On this basis, we define three classes of roles a social agent can play:

- the ***norm source*** is the group or institution which is responsible with the norm setup. A norm source will issue the norms to all member agents of a group and will get feedback knowledge of their decision to comply with any of the issued norms.

- the ***addressee*** is the agent itself: it is able to make a norm decision and to comply with one norm or another from the set of valid norms and in this case it will become a norm *compliant*. It is also free to not comply with any norm, and in this case it will become a *deviant*. For the social learning scenario, both the "*source*" (*stimulator*) agent and the "*learning" (observer) agent* belong to the addressee class.

- the ***defender*** is the agent especially designed to register which member agent does not comply with the norms and to force the compliance of norms in the member agents. The compliance could be enforced by the use of *sanctions*. In the case study on a soccer game simulation this role is actually played by the Arbiter.

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[27] CONTE, CASTELFRANCHI, *Cognitive and Social Action*, UCL Press, 1995.

[28] CONTE, PAOLUCCI, "Intelligent Social Learning", in *Journal of Artificial Societies and Social Simulation*, 4, 1, 2001.

[29] CONTE, DIGNUM, "Social Monitoring and Normative Influence", in *Journal of Artificial Societies and Social Simulation*, 4, 2, 2001.

[30] CASTELFRANCHI, DIGNUM, JONKER, TREUR, "Deliberative normative agents: Principles and architecture", in N.R. JENNINGS, Y. LESPERANCE, *Intelligent Agents VI. Agent Theories, Architectures and Kanguages*, Proc. 6th Internaltional Workshop, (ATAL'99) Orlando, Florida, USA. Berlin/Heidelberg: Springer-Verlag, LNCS 1757., 2000.

A ***norm-oriented behavior*** is a conceptual model for the *social behavior* of an agent in an *artificial normative social system*. It is a representation of the way the agent behaves as a consequence of its option to comply or not with the norms issued by its team. As the individual agent decides to comply with a certain norm in its owner group, its behavior will consequently be influenced by this decision. In the case that the agent decides not to comply with any of the norms issued by its owner group, then it will develop only reactive behaviors without normative influence.

7.2. *The Model of the Social Agent*

The *social agent* is defined as an *aeis* endowed with:

- an identification name,
- an owner class,
- a set of beliefs,
- a set of norms,
- a set of roles the agent can play and their associated competences,
- a set of abstract sensor inputs which provide support for the symbolic communication,
- a communication language and the associated communication techniques and methods,
- norm-oriented behaviors.

7.3. *The Model of a Norm-Oriented s-MAS*

The Artificial Normative Social-like Multi-Agent System (***s*-MAS**) consists of:

- A set of individual social agents described as above;
- A set of owners of the member agents;
- A set of norms on the society system;
- A communication language and symbolic communication methods and technique;
- A set of roles the members play within the agent society (ownership relation);
- A social situation in the agent society.

7.4. *Building-Up Social Knowledge*

One of the aims of the present approach is to show how norm-oriented behaviors are based on knowledge from interaction in artificial multi-agent systems, where by "knowledge" we mean both knowledge about what a norm is and knowledge about what a relation between *norm*, *group membership* and *group goal* represents in a social normative system. The present approach has focused on those social phenomena which may be reproduced or may emerge in artificial social systems as social learning processes. One such social phenomenon is the *social facilitation* as a form of intrinsic social learning[31] in which some agent(s) may be led by other agent(s) to acquire new means for achieving their own goals. In social facilitation models, there is always a source agent, which plays the role of facilitator in stimulating the learning process, and an observer (learning) agent, which actually learns. Learning occurs either as a (i) knowledge acquisition process, (ii) as a behavioral learning process, or (iii) as behavior propagation process. For the observer agent, learning consists in acquiring new means to achieve a goal by providing new relevance to already known data: objects, events or other agents.

The case study focuses on a typical case of social facilitation: *local or stimulus enhancement*. This could provide for two types of attitude emergence: either comply with some norm and learn something about goal achieving or learn the norm itself and extend the interaction state space. The first type is learning by means of *knowledge_from_interaction*[32] and it could either result in a change at the behavior expression level (if the source agent has performed a certain behavior, the observer agent performs the same behavior with respect to its current contextual situation, objects and agents) or it can result in a change at the behavior motivational level (the source agent draws the attention of the observer agent on a certain object/event/agent which favors the latter in achieving its own goals).

The approach builds upon existing ***Dual Dynamics*** (***DD)*** behavior design framework developed by the Behavior Engineering Team of the Fraunhofer AiS Institute for the Robocop agents[33]. The ***DD***-Architecture is a behavior architecture design approach on robot agents[34] [35] [36]. The ***DD***-Architecture is based on *processes* and *quantities*: any agent-environment interaction is represented by means of reactive sensorial and control

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[31] A. BANDURA, *Social learning theory*, Englewood Cliffs, NJ, Prentice Hall, 1977.

[32] C.F. VOINEA, *Agenţi artificiali autonomi: arhitectură, algoritmi, aplicaţii*, Editura Ecologică, Bucureşti, 1998.

[33] This paper reports experimental researches developed while the author was with the Fraunhofer AiS Institute at Schloss Birlinghoven, Sankt Augustin, Germany, in 2001.

[34] H. JAEGER, *The Dual Dynamics Design Scheme for Behavior-based Robots: A Tutorial*, Technical Report, GMD, Sankt Augustin, Germany, 1995.

[35] A. BREDENFELD, H.U. KOBIALKA, "Team Cooperation using Dual Dynamics", in *Proc. of Workshop on* "Balancing Reactivity and Social Deliberation in MAS", ECAI'2000, August 22, Berlin, Germany, 2000.

[36] A. BREDENFELD, "DD-Designer", *AiS.GMD. Review Document*, 2000.

processes resulting in updates of certain resources or quantities represented as local or global variables. ***DD***'s knowledge representation framework is based on several types of processing structures, namely sensor inputs (sensor filters) and two levels of behavioral competence: reactive (elementary) and control (high-level). The math formalism is a set of differential equations which models the reactiveness of the agent to environmental clues and the control over such reactive competences. There is no explicit goal representation. Instead, a *target dynamics equation* states *what* a behavior process should achieve or do, and an *activation dynamics equation* states *when* and *how* certain actions or states should be achieved. The ***DD*** formalism is generalized for complex behaviors by means of *modes*, a concept borrowed from the cognitive science for describing low-level perception-based representations of beliefs[37]. The *mode* concept provides the support for an account on how complex behaviors could be achieved. All behaviors which are active or not active at a given moment of time are represented as a ***mode***. A *belief* in the ***DD*** conceptual model is a *representation* of *all interaction knowledge* the agent has got already from its interactions with the other agents and with the environment. The *social goal* (team goal in the case study) is a normative goal and has an implicit representation in the sense that each high-level norm-oriented behavior is focused on accomplishing the activation constraints imposed from the norm description.

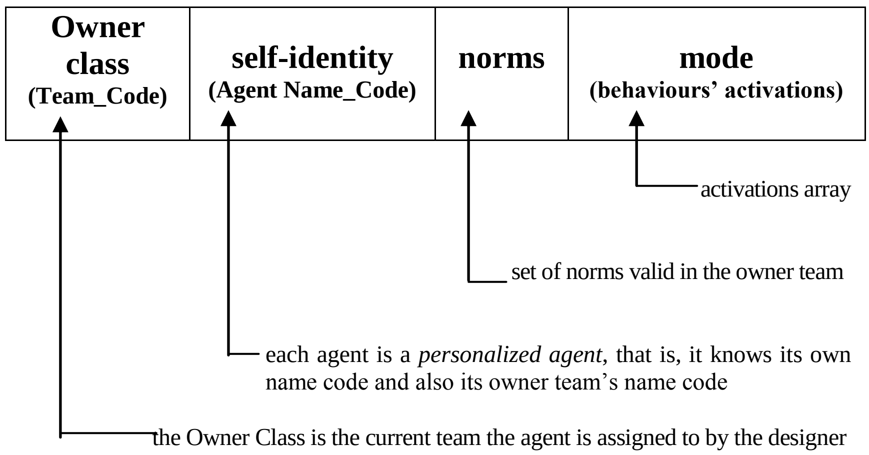

Figure 3. Beliefs dynamic representation in the *DD*-Designer

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[37] *Ibidem.*

7.5. *s-MAS Modeling*

Taking all these into consideration, our first concern was to what kind of **social-like *aeis*** could be designed using the ***DD*** framework. Modeling has focused on the following issues:

(i) representation structure and concepts of the relevant social knowledge like:
   (a) norms as operational behavioral constraints;
   (b) beliefs as enhanced mode representation;
   (c) social sanctions;
   (d) social goals and roles;
   (e) the ownership relations between agents and teams: each agent must belong to a certain team in the sense of the set theory.

(ii) modeling the norm-oriented behaviors: norm-oriented behavior is a social behavior; it is based on inputs from abstract sensors and on social knowledge concerning norm content, role adoption, competence evaluation and social interaction with other agents (communication);

(iii) modeling the high-level "cognitive engines" of the system: (a) the communication language and protocols; (b) the social context; (c) the psychological context.

In this regard, in the ***DD*** representational framework, the cognitive model of a norm is that of an admissible procedural option (*enhancement* or *limitation)* which follows from the condition that each agent *belongs* to a certain team: it is concerned with what the member agent is allowed to do (*enhancement*) and what it is not allowed to do (*limitation* or *restriction*). The *team* is viewed as an *owner class* endowed with certain rights over its members. The *ownership relation* induces in the agent awareness with regard to the norms valid in that team: the agent becomes aware of these norms because they are communicated to all member agents of a team by a *norm source*. From a ***DD****-Designer* point of view, a *norm* has been defined as a *Team Variable*. A set of dedicated *Methods* are used to communicate norms to all team member agents using a *black-board* communication technique. This communication mechanism makes also possible that each agent lets the team know *if* and *what* norm it is currently complying with. This helped at providing the Robocop agents with a generalized well-defined set of dynamical representations and cognitive concepts.

7.6. *The normative social behavior architecture*

Upon the ***DD***-architecture background, the present approach built-up several more levels of representation and behavior, named ***DD+*** (see Figure 3):

- the representations of social knowledge: norms, competences, roles, beliefs, social goals;
- the means to construct and update social knowledge**:** (a) social learning methods and algorithms, (b) communication language;
- the norm-oriented behaviors: the agents comply with one norm or another and this compliance influences all its other behaviors;
- the communication language**:** the agents communicate their name codes, ownership (team) code, current position, competences, roles;
- the emergence of social behavior (attitude): cooperation has been considered such an emergent phenomena; it may come up from the dynamics of the three engines of the *aeis*: reactive, communication and social.

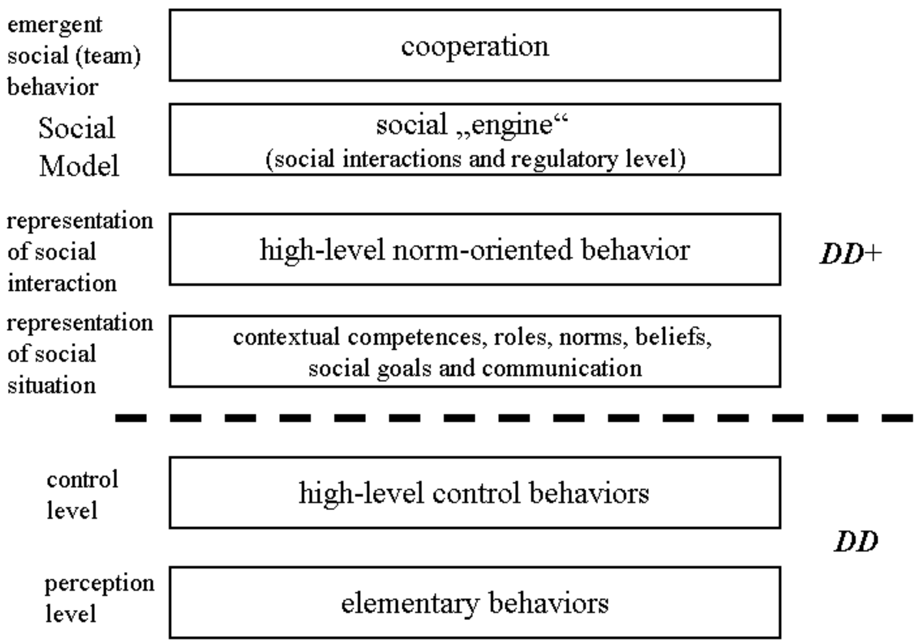


Figure 4. The social normative behavior architecture

8. The Case Study: Social Learning in a Soccer Game Scenario

The case study was meant to answer the question: how *cooperation* could be obtained by using *attitude emergence* in two multi-agent systems involved in a soccer game?

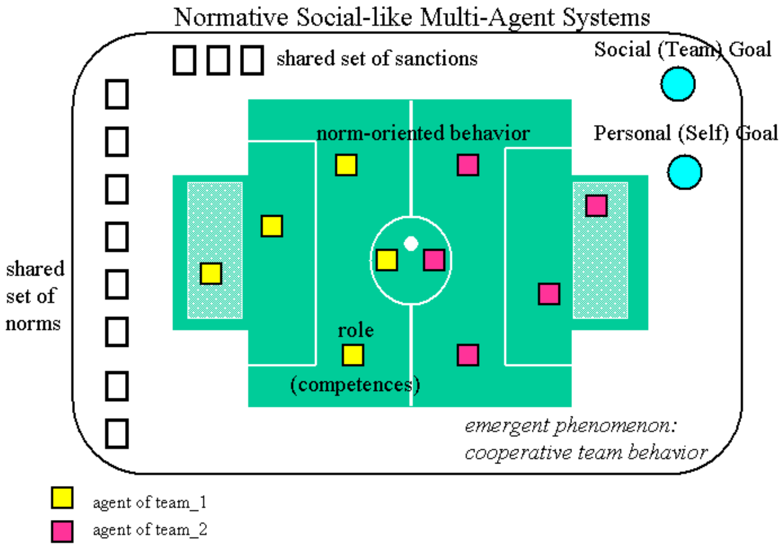


Figure 5. Case Study: Soccer Game

8.1. *Simulation Scenarios*

The implementation of the s-MAS is based on typical situations in a soccer game from which there have been selected ***relevant social facilitation scenarios*** as follows:

1. ***local or stimulus enhancement***: the situation in which one agent has the ball and, due to its role in the field (either as a midfielder or as a forward player), he chooses to pass the ball to its closest neighbour agent which is in the most favorable position for scoring (weak cooperation scenario);
2. ***cooperation between the member players of the same team with respect to the goal***: the agent dynamically assumes a role depending on its position in the field and passes the ball to the closest of its team's members, favoring the latter player in scoring (strong cooperation scenario).

In such a scenario, learning results in:

- acquiring *knowledge* (or *plan*) about the relation between agent's ultimate goal and the active norm set,
- acquiring knowledge about the relation between agent's ultimate goal and its current contextual positioning in the field by evaluating the distances to the closest neighbor agents and the best kicking angles / positions;

- updating the *modes*, which represent the agents' beliefs with respect to the norm-oriented behaviors which they have to perform in order to achieve their goals.

8.2. *AEIS Instantiation as s-MAS*

To this aim, we have used the following instantiation of the ***s-MAS*** model using a set of ***Team Variables*** which are meant to provide the support for the symbolic communication between the member agents of a team, between the member agents and the Arbiter, and between the Norm-Source and the Arbiter. Each Member Agent is endowed with a set of Team Variables which helps the communication process. The set of Team Variables are: the norm-source identification (***Team_Code***), the norms identification (***Norm_Code***), agent identification (***Agent_Code***), the social reinforcers: ***Social_Recognition***, ***Social_Sanction***.

8.3. *AEIS Implementation*

The ***Norm-Oriented Behaviors set*** is meant to represent the high-level behaviors which are developed by the Individual Agents as a consequence of the norm-compliance decision process, whose output is the norm the agent comply with at the current moment of time (***NormCompliance_i***).

Norm compliance in the field results in certain roles the agents dynamically adopt during the soccer game: no matter if the soccer formation type is "attack" or "defense", the players can exchange roles in the field during the game. There have been defined several interaction processes for the following situations:

(i) ***NormCompliance***: the norms are predefined, issued by a norm source which is the team itself;

(ii) ***RoleAdoption***: if the agent moves over certain areas in the field, then a *role change* takes place. Depending on the formation type (attack or defense) and on the position in the field (forward, middle, back, center, wing), the agent will adopt a new role with different competences. If the agent fails in executing its new competences following from the current role adoption, then a social sanction is delivered from the team or from the Arbiter.

RoleAdoption **Process**:
quantities: *competence = 'PassTheBall', role = 'Midfielder'*;
<u>while</u> *ActiveAgent* <u>repeat</u> :
if *role* ← new-role then *competence* ← new-competence

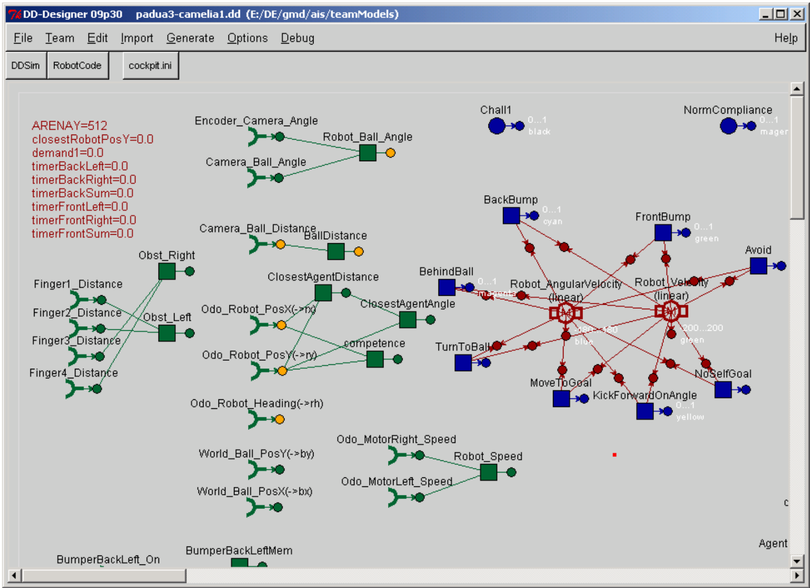


Figure 6. (a) – NormCompliance is a norm-oriented high-level behavior in the ***DD***-Designer

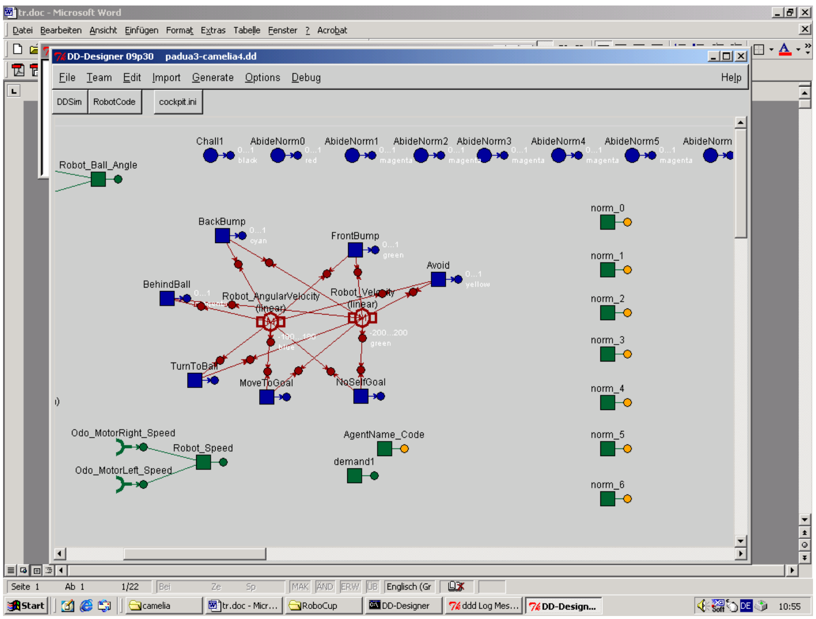


Figure 6. (b) – Norms are defined as Team Variables in the *DD*-Designer[38] (*DD*-simulations performed with the courtesy of the Behavior Engineering Team, Fraunhofer AiS Institute, Germany)

[38] C.F. VOINEA, *Research Report*, Fraunhofer AiS Institute, Sankt-Augustin, Germany, October 2001.

(iii) ***Dynamic Competence Setup***: it is assumed that the agents communicate to each other their identification codes so that they know where they are in the field all the time; this algorithm receives as input the current position of the agent in the field and consequently assigns a specific competence to the player, like: "right wing midfielder", "central midfield", "left wing midfielder", "forward", etc.

Competence_Setup Process:
quantities: *position_in_the_field* M = [**m***ij*]; *competence* C = [**c***ij*], *i = 1,...,X, j = 1,...,Y;*
<u>while</u> *agent_is_in_the_field* <u>repeat</u>:
current_position←(current_X,current_Y);
m(current _X, current_Y) ← **c***ij*

As a consequence, the active agent has to perform a set of high-level behaviors like:

MoveToBall;
TurnToBall;
CommunicateBallPositionToNeighbor;,
FindClosestAgent;
PredictAngle;
KickForwardOnAngle

The activation of these high-level behaviors are representing the *mode*:

*ModeActivationArray=[aNormCompliance_**1**, ..., aNormCompliance_**K**]* (4)

where: *aNormCompliance_**i*** concern the activation of the norm-oriented behavior called "**NormCompliance**_i". The activation array (*mode*) is learned and used in the subsequent observable behaviors of any agent as the background for future behavior expressions.

8.4. *Simulations Analysis*

The learning problem was formulated as follows: given a set of control behaviors, c_i, and a coordination policy, ***k***, the agent learns an *attitude function*, ***A***, by means of a set of coupled control and coordination processes, such that the agent is successfully transferred from the current state to the goal state. The agent learns structural coupling relations in which minimal coordination values, ***att***, are associated to maximum internal rewards values, ***r***. The *learning_while_interacting* method uses the ***cob*** matrix to update the coupled learning processes.

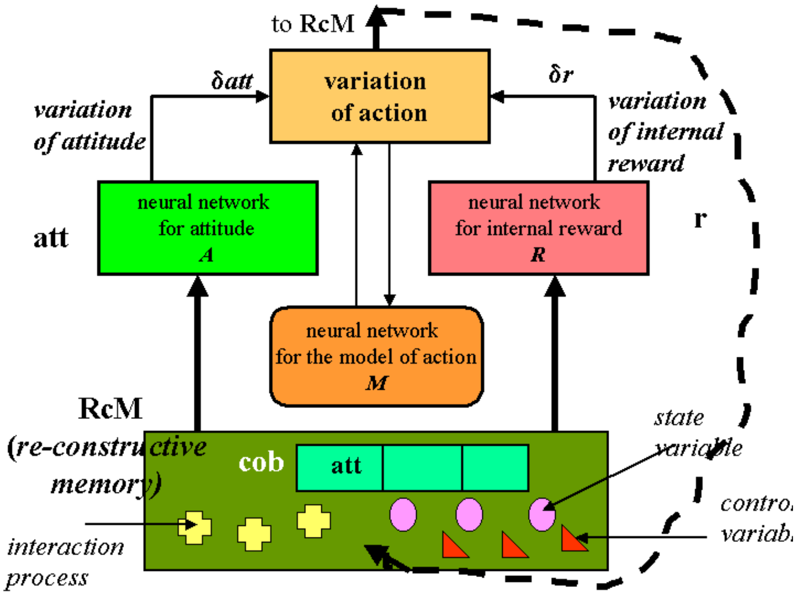


Figure 8. The computational attitude

The computational architecture (see Figure 8) which consists of several neural networks (the ***A***_learning, ***R***_learning and the model_***M*** neural network, respectively) and a re-constructive memory (**RcM**) represented by means of the ***cob*** matrix. Learned variations in control and in the coordination values are used to update the action parameters and to modify the current decision of the player agent. Each learned variation in action is used as knowledge from interaction which updates the re-constructive memory. Behavioral patterns are therefore re-constructed based on the content of the **RcM** during each behavioral cycle[39].

The neural networks require that the agent is trained with a model of attitude, and then left to update this attitude model through learning. The ***cob*** matrix provides a simple way to represent structural coupling relations between behavior control and coordination processes. The behavioral coupling variables (***cob***s) accumulate knowledge about the active behaviors which simultaneously update the same state variable. Provided with both re-constructive and associational mechanisms, each agent starts learning dependencies between behaviors and specific control values. This results in a set of coupling relations which are transmitted from one behavioral cycle to another (within the **RcM** module of each agent) and

[39] EADEM, "Attitude Learning in Autonomous Agents", in *2nd Workshop on Agent-Based Simulation*, Passau, 2001.

from one agent to the other (within the multi-agent system). The behavioral coordination between agents becomes evident when behavioral patterns are re-constructed on the basis of this set of structurally coupled learning processes.

The case study included the weak cooperation and the strong cooperation scenarios. In both of them, the learning task for the agent was to learn to pass the ball on a minimal-length distance to either the closest neighbour team-member agent or to the best positioned in the field team-member agent. Both weak and strong scenarios involved a typical situation of social facilitation. In each scenario, the agent has been previously trained how to pass the ball in order to facilitate either the goal scoring or the advance of another team-member agent to a better position in the field.

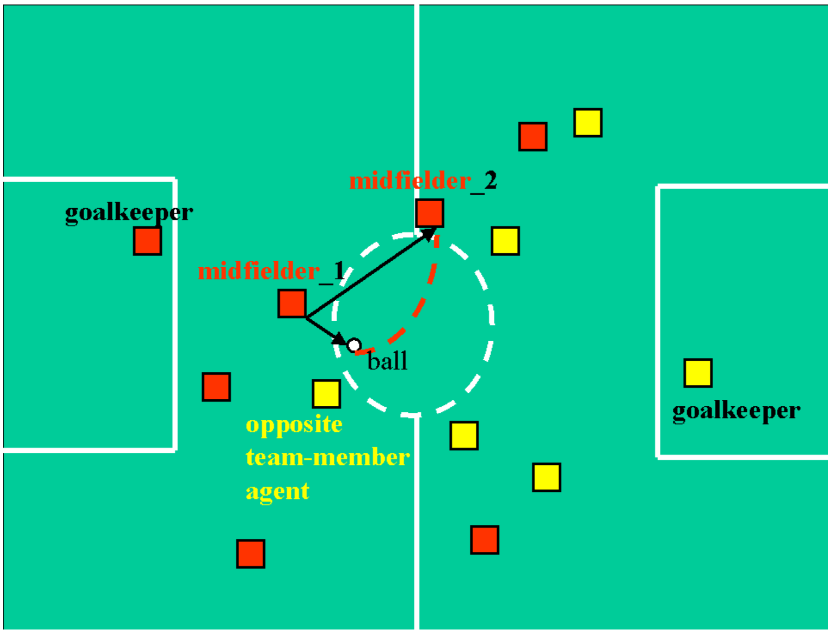
The simulations resulted in two attitude emergence situations: in the weak scenario, the agent learned to co-operate with the closest neighbor team-member agent (see Figure 7a), while in the strong scenario the agent learned to use itself a facilitating position from other team-member agents in order to try scoring a goal (see Figure 7b).

In the former situation the attitude which has emerged was minimizing a *distance_to_the_neighbor* criterion, while the attitude which has emerged in the later situation was maximizing a piece of *knowledge from interaction*, namely a number of cumulative contributions from other team member agents to better positioning the ball with respect to the opposite-team‘s goalkeeper.

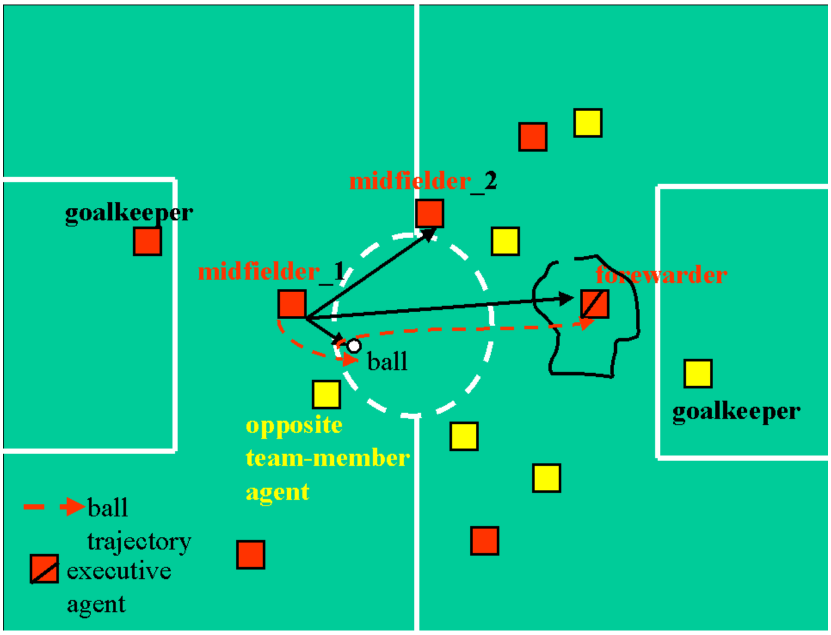
This set of simulations provided evidence with concern to the following issues:

- dynamic representations of knowledge about norm-oriented behaviors, dynamic representations of knowledge about dynamic competence setup and role adoption;
- individual and social determinations of social knowledge building-up process;
- social learning by means of social facilitation, in particular local stimulus enhancement: the agents are able to learn schema of social planning for goal achieving;
- emergence of social cooperation phenomenon in the framework of norm compliance in a social-like normative multi-agent system.

The simulations showed how the soccer players agents learned to pass the ball from one to another as a consequence of their complying with specific norms. The simulations have been successfully performed and showed that the agents are able to improve their game by means of social facilitation schema like the “ball passing”.



(a)



(b)

Figure 7. Social learning in a social facilitation scenario: passing the ball from one member of a team to another member of the same team in the presence of members of the opposite team

9. Conclusions: Interpretation of the Computational Attitude

There are different ways in which computational attitude may be interpreted. This is due to the fact that attitude emergence addresses some fundamental issues: knowledge, interaction, representation, memory and remembering, learning and situated cognition. The basic assumptions and working hypotheses adopted here require an explanation of the philosophical and computational background in the elaboration of the Theory of Attitudes.

The way computational attitude is viewed in this approach is basically as a dynamically built-up representation inside the agent's memory during the interaction with the environment. From a cognitive point of view, the attitude is internally constructed by the aeis agent during learning: it provides for a dynamic representation of the agent-environment interaction at each interaction cycle. However, there is a fundamental difference between the representation means in the classical ML, KR and AI sciences and the representation means introduced in this approach. This difference reside mainly in the use of memory. The traditional view of memory is that of storage device: knowledge is produced and stored in the agent memory for future use and retrieval. To us here, the point memory makes in an aeis agent is the capacity to rather re-construct than re-produce knowledge which arises from the usual interactions. Where does this view come from? – Basically, this view is shaped by the deep belief that our representations are not stored entities, but rather entities which are *produced* as we interact with our world, that is, produced *each time* we interact with the world. This view is enhanced by our type of experience, which builds-up upon our always being in a situation, and upon our having a body. This particular kind of experience would suggest that we are always in a context or a situation which *we carry over from the immediate past and update in terms of events that in the light of this past situation are seen to be significant*[40]. What we actually carry over from the immediate past to the immediate future is not quite a „suitcase" full of pieces of knowledge which we can inspect and search for *that particular one* which we need *now,* but rather *a configuration of our body which lets us know about us and the world all the time,* spontaneously and comprehensively. It is this particular kind of body configuration that makes us able to rather *re-construct* our primary perceptual experience each time anew than retrieve it along fix traces inside our memory[41, 42]. This is not to say that animals or children do not start with certain fixed responses[43], and animals do

[40] M. HEIDEGGER, *op. cit.*

[41] F.C. BARTLETT, *op. cit.*

[42] W.J. FREEMAN, *Societies of Brains*, LEA, 1995.

[43] J. PIAGET, *Biologie et Connaissance: Essais sur les relations entre les régulations organiques et les processus cognitifs,* Gallimard, Paris, 1967.

not often preserve them over a lifetime[44]. It is actually why learning exists at all. The point I want to make in assuming this view is that these responses are subject to permanent variation (even if only a small one!) during the interaction with the environment over their whole lifetime. This is basically why no fix responses or facts with built-in significance remain in an adult human being which are not under the control of a situation. From this point of view, the attitude as defined by the Theory of Attitudes resembles the one described by Bartlett in his account on memory use in human remembering.

The point I wish to make is that, assuming a view of „being-in-the-world“ upon cognition, a way ought to be found in order to prove that there are interaction processes with the environment upon which agents (living agents as well as artificial agents) build-up their cognitive capacity, and that these interaction processes make them cope with the environmental change and often survive this change. I have pursued this idea in the attempt to show that there are behavioral patterns and structure underlying the interaction processes specific to autonomous agents organized as ***aeis****s*.

Future work will develop applications of the above model of s-MAS and representations of norms and social scenarios in order to simulate political leadership and voting behavior.

Acknowledgements

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[44] K. LORENZ, *Behind the Mirror*, 1973.