TOWARDS SEMIOTIC AGENT-BASED MODELS OF SOCIO-TECHNICAL ORGANIZATIONS

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ABSTRACT

We present an approach to agent modeling of socio-technical organizations based on the principles of semiotics. After reviewing complex systems theory and traditional Artificial Life (ALife) and Artificial Intelligence (AI) approaches to agent-based modeling, we introduce the fundamental principles of semiotic agents as decision-making entities embedded in artificial environments and exchanging and interpreting semiotic tokens. We proceed to discuss the design requirements for semiotic agents, including those for artificial environments with a rich enough "virtual physics" to support selected self-organization; semiotic agents as implementing a generalized control relation; and situated communication and shared knowledge within a community of such agents. We conclude with a discussion of the resulting properties of such systems for dynamical incoherence, and finally describe an application to the simulation of the decision structures of Command and Control Organizations.

1. MOTIVATION

Our world is becoming an interlocking collective of **Socio-Technical Organizations (STOs)**: large numbers of groups of people hyperlinked by information channels and interacting with computer systems, and which themselves interact with a variety of physical systems in order to maintain them under conditions of good control. Primary examples of STOs include **Command and Control Organizations (CCOs)** such as 911/Emergency Response Systems (911/ERS) and military organizations, as well as utility infrastructures such as power grids, gas pipelines, and the Internet. The architecture of such systems is shown in Fig. 1, where a physical system is controlled by a computer-based information network, which in turn interacts with a hierarchically structured organization of semiotic agents.

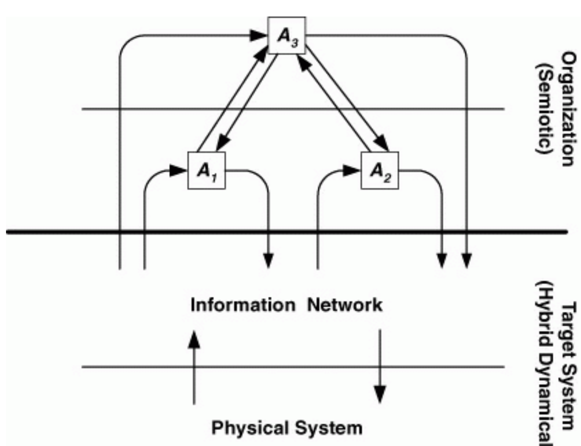

Figure 1: The architecture of STOs.

The potential impacts on planetary economy and ecology are just beginning to be understood. The vast complexity and quantity of information involved in these systems makes simulation approaches necessary, and yet the existing formalisms available for simulation are not sufficient to reflect their full characteristics. In particular, simulations built on strict formalisms such as discrete-event systems cannot capture the inherent freedom available to humans interacting with such systems; and simulations built on formal logic, such as most Artificial Intelligence (AI) approaches, are too brittle and specific to allow for the emergent phenomena which characterize such complex systems.

We pursue an approach to agent modeling which aims squarely between collective automata systems typically used in Complex Systems and Artificial Life (ALife), and knowledge-based formal systems as used in AI. This approach provides a robust capability to simulate human-machine interaction at the collective level. We identify this approach as **Semiotic Agent-Based Modeling**, as it expands the existing **Agent-Based Model (ABM)** approach, as typically used in Complex Systems, with mechanisms for the creation, communication, and interpretation of signs and symbols by and between agents and their environments.

2. COMPLEX SYSTEMS AND AGENT-BASED MODELS

Many researchers are pursuing the hypothesis that ABMs are a highly appropriate method for simulating complex systems.

A **complex system** is commonly understood as any system consisting of a large number of interacting components (agents, processes, etc.) whose aggregate activity is non-linear (not derivable from the summations of the activity of individual components), and typically exhibits hierarchical self-organization under selective pressures.

While almost all interesting processes in nature are cross-linked to some extent, in complex systems we can distinguish a set of fundamental building blocks which interact non-linearly to form compound structures or functions. Together these form an identity whose understanding requires different explanatory modalities from those used to explain the building blocks. This process of emergence results in the need for modes of description which are complementary. It is also known as *hierarchical self-organization*; complex systems are often defined as those which have this property [Pattee, 1973].

Examples of complex systems in this sense are genetic networks which direct developmental processes, immune networks which preserve the identity of organisms, social insect colonies, neural networks in the brain which produces intelligence and consciousness, ecological networks, social networks comprised of transportation, utilities, and telecommunication systems, as well as economies.

Recent developments in software engineering, artificial intelligence, complex systems, and simulation science have placed an increasing emphasis on concepts of autonomous and/or intelligent **agents** as the hallmark of a new paradigm for information systems. Hype has led to the situation where we can identify nearly anything as an agent, from software subroutines and objects, through asynchronous or separately threaded processes, to physically autonomous robots, AI systems, organisms, all the way to conscious entities.

We can recognize two strands of development of the concept of agent in modeling and simulation. The first school draws on examples of complex phenomena from biology such as social insects and immune systems. These systems are distributed collections of large numbers of interacting entities (agents) that function without a "leader." From simple agents, which interact locally with simple rules of behavior, merely responding befittingly to environmental cues and not necessarily striving for an overall goal, we observe a synergy which leads to a higher-level whole with much more intricate behavior than the component agents, e.g. insect colonies and immune responses.

Most such complex systems have been shown to be members of a broad class of dynamical systems, and their emergent phenomena shown to be forms of dynamical attractors (a now classical example is the work of Kauffman [1990]). More famously, ALife [Langton, 1989], a subset of

Complex Systems Research, produced a number of models based on simple agent rules capable of producing a higher-level identity, such as the flocking behavior of birds, which were called Swarms. In these models, agents are typically described by state-determined automata: that is, they function by reaction to input and present state using some iterative mapping in a state space. Such ABMs can be used, for instance, to simulate massively parallel computing systems.

The ABM approach rooted in Complex Systems Research contrasts with the other strand, which draws from AI. In this field, the goal was usually the creation and study of a small number of very complicated actors endowed with a great deal of on-board computational intelligence and planning ability dedicated to solving specific tasks, with little or no room for emergent, collective behavior.

3. Semiotic Agent-Based Models

It has become clear in recent years that the modeling of phenomena such as ecological systems, and social systems such as STOs, requires elements of both the Complex Systems and the AI approaches. First, large human collective systems clearly manifest emergent complex behavior: the emergent constraints created by the coarse dynamics of interaction among agents can dominate overall system behavior and performance.

But a complex systems approach is not sufficient to model social systems. Rather, to model these systems appropriately we need agents whose behavior is not entirely dictated by local, state-determined interaction. A globalized human society, which impacts on planetary ecology, is empowered and driven by language and hyperlinked by information channels. Its agents have access to and rely on accumulated knowledge which escapes local constraints via communication, and is stored in media beyond individual agents and their states. Indeed, many if not most researchers in AI, Cognitive Science, and Psychology have come to pursue the idea that intelligence is not solely an autonomous characteristic of agents, but heavily depends on social, linguistic, and organizational knowledge which exists beyond individual agents. Such agents can be characterized as situated [Clark, 1997]. It has also been shown that agent simulations which rely on shared social knowledge can model social choice more accurately [Richards *et al.* 1998]. We turn to **semiotics**, or the general science of signs and symbols, because the presence of *representations* in such systems is so important. Such representations, either stored internally to the agent or distributed through agent-environment couplings, can be of measured states of affairs, goal states, and possible actions.

Originally a sub-field of linguistics [Eco 1986], semiotics has come to become more prominent first in text and media analysis, and then in biology, computer engineering, and control engineering [Meystel 1996]. Semiotic processes involve the reference and interpretation of sign tokens maintained in coding relations with their interpretants. Thus semiotics in general is concerned with issues of sign typologies, digital/analog and symbolic/iconic representations, the "motivation" (intrinsic relations of sign to meaning) of signs, and mappings among representational systems [Joslyn 1995, 1998; Rocha, 1998b, 1999].

Since models of STOs amount to modeling social networks, our agent designs need to move beyond state-determined automata by including random-access memory capabilities. Our agents are systems capable of engaging with their environments beyond concurrent state-determined interaction by using memory to store descriptions and representations of their environments. They also have access to shared knowledge amongst the members of their particular agent society. Such agents are *dynamically incoherent* in the sense that their next state or action is not solely dependent on the previous state, but also on some (random-access) stable memory that keeps the same value until it is accessed and does not change with the dynamics of the environment-agent interaction. In this sense, our agent designs create ABM which bridges traditional Artificial Life ABM and AI knowledge-based approaches.

4. Design Requirements for Semiotic Agents

As we mentioned above, there are a variety of senses of the term "agent" available the literature today, deriving from, for example, biology, robotics, ALife, and AI, and having applications in information systems, dynamical systems simulation, and natural systems simulation. In this section we lay out our sense of **Semiotic Agents (SAs)**, and make a principled argument about the necessary components for SAs interacting with each other and within artificial environments.

First, what are the necessary components of agents in general? Commonly cited properties include asynchrony, interactivity, mobility, distribution, etc. In general, we can see that an agent must possess some degree of *independence* or *autonomy*, and gain identity by being distinguishable from its environment by some kind of spatial, temporal, or functional boundary [Joslyn 1998, 1999]. In seeking out a specific and useful sense of "agent", we require that they have some autonomy of *action*, an ability to engage in tasks in an environment without direct external control.

Thus our concept of an SA distinguishes agents specifically as *decision-making* systems. These have a sufficient freedom over a variety of possible actions to make specific predictions of the outcomes of their actions. Clearly this class includes AI systems, but leaves out many simpler collective automata or state-transition systems typical of ALife. However, as discussed above, we are interested not in individual agent decision-making capabilities, but rather in the complex, emergent, collective behavior of populations of decision-making agents with access to simple personal and shared knowledge structures. That is, we propose multi-agent system designs that use techniques from AI, but in an enlarged Alife setting.

We thereby further distinguish SAs from pure decision-making algorithms [Wolpert *et al.* 1999], in that they are embedded in (hopefully rich) virtual environments in which they take actions which have consequences for the future of the agents themselves. These environmental interactions induce constraints on the freedom of decision-making on the part of the SAs, and produce emergent behavior not explicitly defined in the agents' (decision-making) rules of behavior.

4.1 Artificial Environments: The Selected Self-Organization Principle

In ABM, agents interact in an artificial environment. However, it is often the case that the distinction between agents and environments is not clear. In contrast, in natural environments, the self-organization of living organisms is bound and is itself a result of inexorable laws of physics. Living organisms can generate an open-ended array of morphologies and modalities, but they can never change these laws. It is from these constant laws (and their initial conditions) that all levels of organization we wish to model, from life to cognition and social structure, emerge. These levels of emergence typically produce their own principles of organization, which we can refer to as rules, but all of these cannot control or escape physical law and are "neither invariant nor universal like laws" [Pattee, 1995, page 27].

For ABM to be relevant for science in general, the same distinctions that we recognize in the natural world between laws and initial conditions determined in the environment, and emergent rules of behavior of the objects of study, need to be explicitly included in an artificial form. Thus the most important consideration is that simulated agents operate within environments which have their "laws of nature" or "virtual physics". From these, different emergent rules of behavior for agents can be generated and studied. As we have argued elsewhere [Rocha and Joslyn, 1998], these need to be explicitly distinguished in artificial environments.

Once this distinction is recognized, then the freedom of decision making which the SAs have is necessarily constrained by these environmental dynamics which are, for them, necessary. Such constraints can be, in fact, crucial for the development of emergent properties within agent systems embedded in those environments. For example, Gordon, Spears, *et al.* [1999] have simulated distributed sensor grids exploiting an agent model interacting with an environment which manifests a certain limited virtual physics. They have shown that they can achieve hexagonal or square grids based on the dynamics of the agent interactions with those "natural laws". Similarly, Pepper and Smuts [1999] have demonstrated the development of cooperative and altruistic behavior in simulated ecologies, but *only* when the environment had a rich enough "texture" of simulated vegetative diversity.

Therefore, the setup of environments for multi-agent simulations needs to:

i **_Specify the dynamics of self-organization_**: specify the laws, and their initial conditions, which characterize the artificial environment (including agents) and the emergence of context-specific rules. For example, in Lindgren's [1991] experiments, the laws of the environment are the conditions specified in the iterated prisoner's dilemma and a genetic algorithm – these are inexorable in this model. The context-specific rules are the several strategies that emerge whose success depends on the other strategies which co-exist in the environment and therefore also specify its demands together with the laws. However, the same laws can lead to different transitory rules, and thus, different agent environments.

ii **_Observe an emergent or specify a constructed semantics_**: identify emergent or pre-programmed (but changeable) rules that generate agent behavior in tandem with environmental laws. In particular, we are interested in the behavior of agents that can simulate semantics and decision processes. As an example consider the experiments of Hutchins and Hazlehurst [1991] which clearly separate between the laws of an environment (the regularity of tide and moon states) and the artifacts used by agents to communicate the semantics of these regularities among themselves. The semantics of the artifacts are not pre-specified but emerge in these simulations.

iii **_Provide pragmatic selection criteria_**: create or identify a mechanism of selection so that the semantics identified in *ii* is grounded in a given environment defined by the laws of *i*. These selection criteria are based on constraints imposed both by the inexorable laws of the environment and the emergent rules. When based only on the first, we model an unchanging set of environmental demands (explicit selection), while when we include the second, we model a changing set of environmental demands instead (implicit selection). The first are often implemented by a Genetic Algorithm (GA) with fixed evaluation function, while the second with a GA whose evaluation function emerges from agent interactions [e.g. Ackley and Littman, 1991].

These three requirements establish a *selected self-organization principle* [Rocha, 1996, 1998a] observed in natural evolutionary systems. This principle is also essential to model the emergence of semantics and decision processes in ABM which can inform us about natural world phenomena. This is because without an explicit treatment or understanding of these components in a simulation, it is impossible to observe which simulations results pertain to unchangeable constraints (laws), changeable, emergent, constraints (rules), and selective demands. It is often the case in Artificial Life computational experiments that one does not know how to interpret the results – is it life-as-it-could-be or physics-as-it-could-be? If we are to move these experiments to a modeling and simulation framework, then we need to establish an appropriate modeling relation with natural agent systems which are also organized according to laws, rules, and selection processes.

4.2 Semiotic Agents

SAs as we see them need to be based on a few fundamental requirements. The primary internal components of semiotic agents involve a series of *representations*, in particular representations of the current state and past states (the agent's "beliefs"), and the goal state (its "desires"). This is partly motivation for usage of the term "semiotic", since we draw from a number of principles from this general science of representations.

i **_Measurement_**. Only certain aspects of the environment are measurable by agents, and this repertoire forms the potential field of knowledge for the agent, its "world as perceived".

ii **_Capacity to evaluate current status_**. Since a goal of ABM of social systems is to study decision processes, our agents need to include a means to describe their own preferences and beliefs about their perceived world. Thus agents need to have separate behavior components for action and evaluation. The evaluation component is used by the agent to judge, based on its own beliefs, its current status in the environment and then influence the action component. These components can be created and/or evolved independently. In this way we can model agents with different, independent beliefs about their present state and desirable goals. This capacity is present in the agents of Ackley and Littman[1991] (which are similar to those of Werner and Dyer [1991] and Hutchins and Hazlhurst [1991]). However, our evaluation components are further constrained by shared knowledge structures and situated communication below (*v* and *vi*).

iii ***Stable, decoupled memory***. To model more realistically decision processes, and achieve greater dynamical incoherence between agents and environments, we need to move from state-determined behavior components and endow agents with larger, random-access, memory capacity. This implies the storage of a set agents' interactions in memory to aid its evaluation and action behavior (*ii*). These memory banks persist and can be accessed at any time by the agent, not depending on its current state or the state of the environment.

iv ***Asynchronous behavior***. In our models, agents do not simultaneously perform actions at constant time-steps, like cellular automata or boolean networks. Rather, their actions follow discrete-event cues or a sequential schedule of interactions. The discrete-event setup allows for inter-generational transmission of information, or more generally, the cohabitation of agents with different environmental experience [Ackley and Littman, 1991; Werner and Dyer, 1991]. The sequential schedule setup, formalized by **Sequential Dynamical Systems (SDS)** [Barrett *et al.*, 1999], allows the study of different influence patterns among agents, which are very important in studying decision processes in social networks. The latter are ideal for mathematical treatment as different schedules can be studied in the SDS framework, while the former require statistical experimentation as the collective behavior of discrete-event agents in an environment with stochastic laws and rules cannot be easily studied mathematically.

These four design requirements cast SAs as decision-making systems, but embedded in the artificial environment and endowed with action capabilities with respect to that environment. Thus in turn the possible decisions that agents can make must be considered relative to those possible actions. The result of all of this is that SAs can be cast in terms of a **generalized control architecture**, as in the work of Powers [1973, 1989], where the autonomy of the system is allowed by its manifestation of a closed causal relation with its environment. Through this relation the agent makes decisions so as to make its measurements (representations of current and past decisions and states) as "close" as possible to its goals in order to reduce a generalized "error function" given by its own beliefs of what desirable states are. Thus, as illustrated in Fig. 2, SAs manifest a generalized negative feedback control relation.

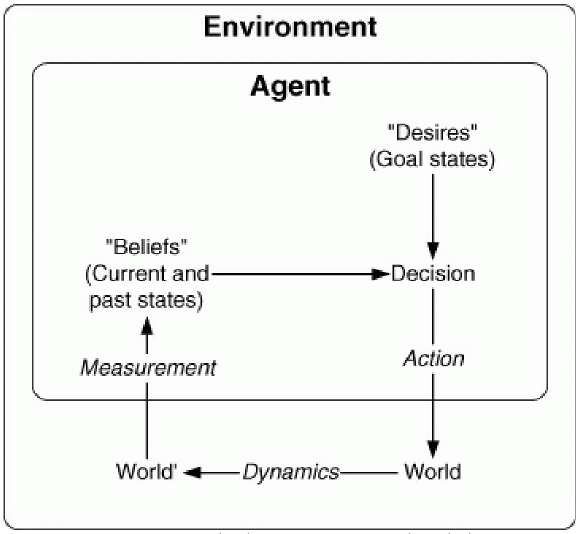

Figure 2: Semiotic agents as maintaining a generalized control relation with their environments.

Furthermore, the dynamical incoherence of SAs allows a degree of freedom from state-determined responses, thus endowing them with a limited form of deliberation or election, the autonomy of action necessary for emergent agent-based models of collective social behaviors. The asynchrony requirement allows also for more realistic social agent interaction, where decisions are taken by integrating the decisions of others and the co-existence of agents with different experiences is allowed.

4.3 Situated Communication and Shared Knowledge

While in the previous subsection we have described the properties and capabilities of SAs in isolation or in interaction with the artificial environment, we also require their interaction through the production, transmission, and interpretation of informational tokens. Thus the decision-making and communication abilities of SAs observe the two additional design requirements:

v ***Situated Communication***. Communication among agents is based on the existence of environmental tokens and regularities which follow the laws of the environment and agent rules, not merely unconstrained, oracle-type, universal channels [Hutchins 1996; Hutchins and Hazelhurst 1991]. Both within and between agents, knowledge about the environment will be represented by distinct tokens in certain modalities, perhaps qualified by uncertainty structures. Tokens can be created, transmitted, received, stored, and (most importantly) interpreted by agents. Tokens created from measurement processes can simply be stored in memory or interpreted directly by the agent, either currently or at a later time. Tokens need not be simple, atomic units, as elements of a set, but can also be at least somewhat complex, for example simple graph-theoretical structures or uncertainty-weighted atoms or distributions.

vi ***Shared and cultural nature of language and knowledge***. We require that agents share a certain amount of knowledge. In this way, agents are not completely autonomous entities with their own understanding of their environments. We are interested in studying social systems which strongly rely on shared knowledge expressed in public languages. Often in agent-based models agents reach decisions relying solely on "personal" rules and knowledge-bases. This autonomous view of agency is unrealistic when it comes to modeling cognitive and social behavior, as ample evidence for the situated nature of cognition and culture [Clark, 1997; Richards et al, 1998; Beer, 1995; Rocha, 1999]. Therefore, our agents build on the graph structures used by Richards *et al.* [1998] to model shared knowledge. In particular we expand this framework with the asynchrony (*iv*) and situated communication (*v*) agent design requirements. We also study emergent shared knowledge structures. SAs make use of shared knowledge in addition to personal knowledge which exists in the form of beliefs and goals described in *ii*, which can be built-in or emergent rules as discussed in 4.1.ii.

5 Semiosis and Dynamical Incoherence

Clearly, the multi-agent systems with the requirements above possess elements of both dynamical coherence and incoherence. The dynamic laws of the environment (4.1.i) spawn rules of agent behavior (4.1.ii) which are this way dynamically coupled to the environment. The dynamical incoherence occurs because of the following semiotic requirements:

A. Shared knowledge structures which persist in the environment through at least for long intervals of dynamic production (4.2.vi);
B. The stable memory banks used by agents to store knowledge are decoupled from the dynamics of the environment (4.2.iii);
C. Semantic tokens used by situated communication, which persist in the environment, at least for long intervals of dynamic production, until they are picked up by agents (4.2.v);
D. The pragmatics of the selection criteria in an environment (4.1.iii) may erase or increase the numbers of certain agents, thus intervening in the dynamics of the environment in a switch or catalyst-like manner (non-holonomic constraints [Pattee, 1973])

Note that the asynchrony requirement (4.2.iv) does not necessarily imply dynamical incoherence. Discrete-event or schedule-driven agents may or may not respond to their cue events or schedules in a dynamically incoherent manner. If their action and evaluation components are state determined, as the agents of Ackley and Littman or the SDS framework, then they are still dynamically coupled to their environment and its cues. It is only the semiotic requirements above which can create a degree of dynamical incoherency, as memory gets decoupled from state-determined interaction and selection constraints the dynamics of an environment "from-the-outside". D is clearly a pragmatic semiotic requirement, whereas A, B, and C are both semantic and syntactic requirements. The syntax is not obvious, but it must be subsumed in the rules of communication agents use to access shared knowledge structures and participate in a situated communication process.

Finally, we can see that semiotic ABM draw from Discrete-Event Simulation, AI, Complex Systems and ALife. From Discrete-Event Simulation [Zeigler 1990], we require asynchrony, but unlike traditional simulation, we use the distributed ideas of complex systems, requiring that agents do not push for or understand an overall goal, which only emerges from agent interactions. From AI, we require agents with access to memory structures (beyond state-determinacy), and semiosis.

6. Simulating CCOs

Our research project with the Physical Science Laboratory at NMSU is intended to simulate the emergent decision structures in a 911/ERS, seen as an example of a CCO. CCOs in general are characterized by a number of properties, including a large number of units which are hierarchically organized, both for information flow upward and command flow downward; where the lowest level units are individual humans, perhaps in vehicles; the organization must achieve a goal within a distinct time and within a physical environment; and the environment may or may not contain other organizations with which the CCO interact. At the time of this writing, we are simultaneously pursuing initial agent designs consistent with the concepts outlined above, and evaluating a number of software platforms for developing prototype agent simulations, including Swarm, DEVS/JAVA, and JAMES.

We conclude by highlighting some issues particularly important to using our semiotic agent approach to simulating CCO:

- **Negotiation vs. Situational Awareness:** Within CCO there is an acting distinction between "background" communication ("autonomic" traffic) concerning the situational awareness about the location of other units, terrain, etc; and "foreground", direct communication (whether voice, text, or image) among units to make reports, give commands, and otherwise negotiate the current situation. Background communication, although also mediated by a digital network, should be considered a *measurement* task (the unit's ability to observe its environment is augmented by the digital SA capability), while foreground communication should be considered a *communication* task.

- **Hierarchical Organization:** The ability to aggregate information upwards and distribute command downwards in CCOs is crucial. We are exploring alternate forms to strictly hierarchical tree structures, involving loosely hierarchical directed acyclic graphs and flexible structures where command is assumed temporarily by internal units. In this way, command becomes understood as a generalized constraint on the decision processes of agents.

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