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The semiotics of control and modeling relations in complex systems☆

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Abstract

We provide a conceptual analysis of ideas and principles from the systems theory discourse which underlie Pattee's semantic or semiotic closure, which is itself foundational for a school of theoretical biology derived from systems theory and cybernetics, and is now being related to biological semiotics and explicated in the relational biological school of Rashevsky and Rosen. Atomic control systems and models are described as the canonical forms of semiotic organization, sharing measurement relations, but differing topologically in that control systems are circularly and models linearly related to their environments. Computation in control systems is introduced, motivating hierarchical decomposition, hybrid modeling and control systems, and anticipatory or model-based control. The semiotic relations in complex control systems are described in terms of relational constraints, and rules and laws are distinguished as contingent and necessary functional entailments, respectively. Finally, selection as a meta-level of constraint is introduced as the necessary condition for semantic relations in control systems and models. © 2001 Elsevier Science Ireland Ltd. All rights reserved.

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1. Introduction

Consider the most central questions of modern interdisciplinary science, or "natural philosophy", including the following:

- How do we understand the use of the concepts of order, organization, complexity, information, etc., in systems of various types? How can they be characterized and measured?
- What is the nature of information as distinct from matter and energy in the natural world, how does it arise, and how is it incorporated into systems?
- How can these concepts be used to create interdisciplinary scientific theories finding common structures and evolutionary processes in socio-technical, ecological, psychological, biological, and physical systems?

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When we consider these questions in general, and then in specific systems across the full cosmic range of time scales, the problem of the origins of life appears to provide a central focus. It is here that we first see the appearance of the controlled organization of matter, of evolutionary processes leading to a cascading hierarchy of increasing complexity at emergent levels above the physical, of the codification and use of information in systems, and of control and modeling processes internal to systems.

It has been proposed in the modern biosemiotics school that the problem of the origins of life is equivalent, or at least coextensive, with that of the origins of control, semiotic relations, or symbolic or semantic information (Deely, 1992; Hoffmeyer, 1996; Joslyn, 1998). In this context, concepts of statistical (Pattee, 1973), semantic (Pattee, 1982, 1995), or semiotic closure has provided a central touchstone not only for theoretical biology, but also in systems theory and cybernetics for understanding the broader series of evolutionary systems.

The linkage of concepts and literature from general systems theory and cybernetics on the one hand, and semiotic theory on the other, is quite welcome, as it serves to elucidate ideas from both. For example, the relationship of systems and information theoretical concepts of organization and complexity benefit greatly when combined with those of semantics, meaning, and interpretation from semiotics. Perhaps the best place to see this synthesis is the rich literature (e.g. Powers, 1973; Turchin, 1977; Rosen, 1985; Campbell, 1987; Cariani, 1989; Rosen, 1991; Joslyn, 1997; Cariani, 1998), traceable back to the founders of systems theory and cybernetics in the post-war period (Ashby, 1956), which has tried to construct a coherent philosophy of science based on two fundamental concepts:

- *Models* as the basis not only for a consistent epistemology of systems, but also as an explanation of the special properties of living and cognitive systems.
- *Control systems* as the canonical form of organization involving purpose or function.

While controls and models are distinct kinds of organization, what they share is a common basis in semiotic processes, in particular the use of a measurement function to relate states of the world to internal representations. Perhaps for this reason there has been some ambiguity in the literature about the specific nature of controls and models, and more importantly how they interact. This has led to confusion, for example, about the role of feedback vs. feedforward control, about endo-models *within* systems vs. exo-models which we as observers construct *of* systems, and about the various forms and natures of circular causality.

In this paper, we seek to explicate the nature of control and modeling relations in systems of all types, as a first step to understanding their origin, development, and evolution. We begin by laying out the conceptual foundations of any control system from a semiotic perspective. We contrast the control relation with the modeling relation, which forms the other canonical semiotic relation between a system and its environment. These share the fundamental semiotic measurement, or perception, functions, but are contrasted by their linear and circular topologies, respectively. Hybrid and hierarchical representations are developed, casting the modeling relations within the context of an active control system.

The relations present in control systems and models can be understood in terms of the fundamental cybernetic concepts of variety and constraint among classes of phenomena. We will see how semiotic concepts such as syntactic and semantic relations can be understood as forms of constraint in this relational sense. What is especially interesting is when there is the ability for a constraint to be itself variable at a higher level of analysis. This allows recovery of selection as a form of constraint on a pragmatic basis (whether through natural evolution for survival or by human design to perform functions we desire), which is the hallmark of semantic relations and the presence of a semiotic system.

Finally, after unpacking these concepts to this level, we are able to come to a better understanding of the concepts at stake in various formulations of semantic or semiotic closure.

2. Preliminaries

We begin with some preliminary considerations.

2.1. Complementarity of models

Below we explicate the nature of semiotic relations, and models and controls in particular. These concepts are so fundamental to the modern cyber-semiotic perspective that it is difficult to do this in a "foundationalist" way, separating the axioms cleanly from the conclusions. In particular, we use the concept of a "model" below in at least three complementary ways. First, models in the abstract sense are explicated in Section 3.1. Then, "endo-models" are introduced in Section 5.3 as internal components of complex control systems, which anticipate future states.

But in addition, it should be understood that we agree with Sebeok (1988) that semiotics demands or creates an overall "cybernetic theory of modeling" wherein all knowledge (including, for example, this paper) is seen as a form of model-building on the part of organisms and subjects. Thus in particular, each of the concepts explicated and diagrammed below is understood to be itself an "exo-model", constructed by an abstract observer (a surrogate for the author), of some particular representation or view of a hypothetical class of systems.

2.2. Diagrammatic approaches and category theory

Our approach is inspired in some ways by the direction of Rosen (1991) and others ho have suggested category theory was a new canonical language for systems theory (Goguen, 1991) and relational biology (Louie, 1985). They assert that category theory's invocation of relational concepts and graph theoretical and graphical (in the sense of visual) representations is more appropriate than set theory for representing the complex relations in systems (Joslyn, 2001). While we do not use category theory per se, we do make our arguments here using primarily abstract, but semi-formal, diagrams representing relations of various types. We hope that further consideration can lead to a more formal treatment in the future.

2.3. Perspective on semiotics

Our approach is fundamentally from within the discourse of systems theory and cybernetics and its perspective on information theory as a potential grounding for a universal science (Klir, 1991). However, we believe that semiotics is required to be injected into that discourse to provide a richer perspective on the use and nature of information in descriptions of real systems. We acknowledge the value of the post-modern perspective on "second order cybernetics" and its emphasis on the necessary relativity of all descriptions to a collection of coherentist observational frames provided by interacting subjects. But similar to Umpleby (1989), we also remain committed to the value of formal foundations which describe aspects of reality for the accomplishment of particular purposes to some level of accuracy or specificity. As such we draw our semiotic grounding not from any particular school or theory, but liberally from modern approaches which attempt to merge semiotics with formal representations of information, as in the work of Eco (1979), Dretske (1982), and Meystel (1996).

2.4. Systems foundations

Our approach is rooted in general systems theory, which seeks to describe the general classes of relations which systems can have with their environments. We recognize (Joslyn, 1995, 2000) both the "structural" view of systems as holistic collections of interacting parts (as in the multi-dimensional relational approach of Mesarovic and Takahara (1988)); and the "constructivist" view which avoids concepts of existing entities with objective attributes, instead defining a system as a bounded region of some (perhaps abstract) space which functionally and uniquely distinguishes it (Spencer-Brown, 1972; Goguen and Varela, 1979). Both views entail an explicit expression of the concept of the boundary or distinction between system and environment, and thus in all instances we consider only a frame of reference fixed to a particular given system–environment coupling or distinction.

As shown on the left of Fig. 1, a single system is considered coupled to an "absolute environment". Of course, the labels could easily be inverted. Indeed, the recognition of abstract "environments" relative to "systems" is thus somewhat arbitrary, depending perhaps on the observer's perspective or on the relative spatial or temporal scales present.

Also, systems come in collections, or "societies", which can make the system–environment distinction or coupling complex. In particular, as shown on the right of Fig. 1, systems in collections interact with "relative environments" consisting of the "physical" environment as well as all the other systems. This formulation can also be somewhat arbitrary, but will be useful to us below in Section 4.2.

2.5. Throughputs and closures

Consider a single system S coupled to its environment E. In the structural view S and E are represented as multi-dimensional mathematical relations. When at least one dimension in both S and E participates as informational or relational flows through the system–environment boundary, then S and E can be cast as input/output systems.

Denote g: $E \mapsto S$ as the (abstract) relations from the environment to the system, and f: $S \mapsto E$ as those back from the system to the environment. In any particular system–environment coupling such relations are interpreted in particular ways, for example as entailments, forces, influences, etc.

Logically, we can then recognize only two general forms of these relations:

- When the inputs and outputs of f and g are distinct, then we recognize only input/output relations which flow through the boundary in one or the other direction. These we will call *linear* (in the sense of "one way", not to be confused with linear algebraic or dynamical systems), and the systems *throughputs*.
- When the outputs of f are (or significantly affect) the inputs of g, we recognize the relations as *circular*, and identify the systems as *closures*.

These fundamental concepts of throughputs and closures have dominated the systems literature (Joslyn, 2000). In particular, they raise directly the issues of the possibility or necessity of such phenomena as circular causality, which is so central to the cybernetics community (von Förster, 1981); of self reference (Löfgren, 1990); and self production, both as autopoeisis (Zeleny, 1981) and autocatalytic biochemistry, as contributing to the origins of life (Eigen, 1992).

2.6. Constraint concepts

As noted, we seek to delve into the foundations of controls and models from a systems-semiotic perspective relying on informational concepts. In our experience, working with such apparently simple concepts is in fact fraught with hidden complexities. Thus we have found (Joslyn, 1992; Heylighen, 1995; Klir and Wierman, 1999) great value in seeking out other concepts foundational

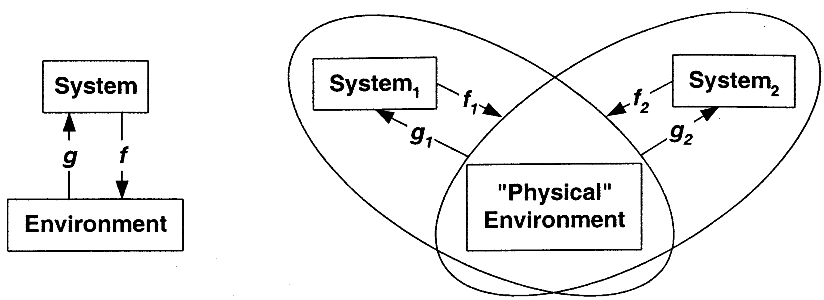

Fig. 1. (Left) A system coupled to an absolute environment. (Right) Systems interacting with relative environments containing other systems.

to these. Returning to our systems foundations, we build on abstract relations among classes of phenomena as in mathematical systems theory. Such relations can be understood as collections of distinctions amongst values of states (for example, in discrete or continuous state spaces). Variety is then the quantity of distinctions, and thus characterizes the relative freedom of such relations.

Constraint is a central concept to our understanding, and it is important to explicate our sense of it specifically. In the most general sense, "constraint" is any restriction or limitation. An important special sense in this discourse is that of a "physical constraint" in a physical problem. Examples of such physical constraints include boundary or initial conditions in dynamical systems. Another important category to this discourse are "non-holonomic" physical constraints (Rosen, 1985) which act on higher-order derivatives in physical systems.

We will primarily rely on the sense of "relational constraint" from mathematical systems theory (Mesarovic and Takahara, 1988) as a reduction in the state space actually populated in a mathematical description of a problem (physical or otherwise). In our context, relational constraint is interpreted as the degree of restriction or determinism of the variety of some relation. Note that physical constraints imply relational constraints in the mathematical representations of the problems they are physically constraining, but not vice versa. This will be returned to in Sections 6.2 and 6.3 below.

2.7. Representations

The concept of "representation" is also central to us, and we use it while also recognizing both its ubiquity and its difficulty in the literature. We mean to imply the existence of a particular input relation (a relational constraint) from the environment to the system. The representation is then produced as some phenomenon of stability or regularity internal to the system which captures or maps some corresponding environmental regularity. This is close to an abstract semiotic sense of "sign-vehicle" or "sign-token", in that the representation is the physical phenomenon which

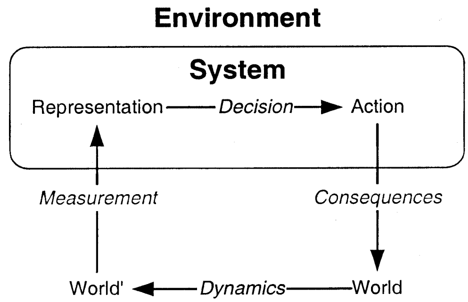

Fig. 2. Functional view of a control system.

stands for the corresponding environmental regularity. In some cases we will specify the representation more finely to be a particular kind of sign-vehicle (for example, a symbol token). Otherwise, the reader should assume a more generalized concept of representation.

3. Simple control systems and models

In systems theory and cybernetics the modeling relation and the control relation serve as two fundamental and distinct classes of semiotic relations between a system and its environment, or "the world".

3.1. Simple control systems

Consider first a classical control system as shown in Fig. 2. In the world (the system's environment) the dynamical processes of "reality" proceed outside the knowledge of the system. Rather, all knowledge of the environment by the system is mediated through the measurement (perception) process, which provides a representation of the environment to the system. Based on this representation, the system then chooses a particular action to take in the world, which has consequences for the change in state of the world and thereby states measured in the future.

To be in good control, the overall system must form a negative feedback loop, so that disturbances and other external forces from "reality" (for example noise or the actions of other external control systems) are counteracted by compensating actions so as to make the measured state (the representation) as close as possible to some desired state, or at least stable within some region of its state space. If rather a positive feedback relation holds, then such fluctuations will be amplified, ultimately bringing some critical internal parameters beyond tolerable limits, or otherwise exhausting some critical system resource, and thus leading to the destruction of the system as a viable entity.

Fig. 2 is a functional view of a simple control system, representing the logical relations among certain components of the system and the world: the nodes are logical constructs and the arrows are labeled by the kind of relations which hold between them, or the nature of the constraint one places on the other.

In other words, the measurement function relates a state of the world to a particular representation through one kind of constraint; a decision function (by some agent) relates that representation to the choice of a particular action by another; that action has consequences for the state of the world (through some dynamical constraint); and then in the world other dynamical constraints produce future states of the world.

Alternatively, a structural version of the same diagram can be constructed as shown in Fig. 3, representing now the physical entities in the system and the world and how they are structurally related: the nodes are now subsystems which perform certain physical processes, and the arrows are labeled by how they interact. Thus the physical sensors interact with the state of affairs in the world to produce a representation (token) which is passed to the agent which executes a decision to choose a particular action taken in the world.

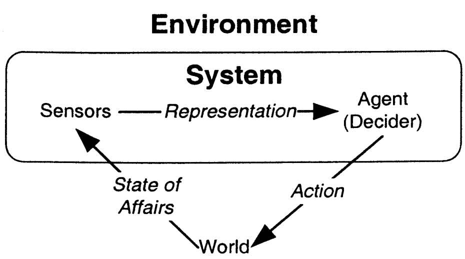

Fig. 3. Structural view of a control system.

Table 1
Functions sufficient for semiotic control

x	$f_1(x)$	$f_2(x)$	$f_3(x)$
+	d	d	d
−	u	u	u
0	n	d	u

Note how generally the functional and structural views are dual: nodes in one are generally arrows in the other, and vice versa.

A simplified, discrete example will help here. Let O be a trivial organism which lives near an oceanic thermocline with warm water above and cold water below. O acts as a control system in relation to the thermocline. We can identify the components of the functional description of a simple control system. The properties of the thermocline are the states of the world and its dynamics. The measurement relation maps these states to a representation of a single critical variable of temperature, with symbolic states

$$X = \{+ = \text{“too hot”},\ - = \text{“too cold”},\ 0 = \text{“just right”}\}.$$

O can affect a single discrete action with possibilities

$$Y = \{u = \text{“go up”},\ d = \text{“go down”},\ n = \text{“do nothing”}\}.$$

The decision relation is a function f: $X \mapsto Y$. The consequences are as expected: the action u raises and arms O, the action d lowers and cools it, and n does nothing.

There are $3^3 = 27$ possible decision functions f, any of which the agent could invoke to make a decision to take a particular action. But only the three shown in Table 1 will result in stable negative feedback control. f_1 is the best default selection, since it minimizes unnecessary action and results in smoother and faster control. But if f is not selected from these three, then positive feedback, not negative feedback, will result, with a corresponding runaway behavior: O either freezes or boils.

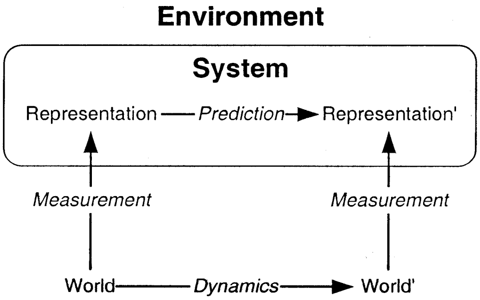

Fig. 4. Functional view of the modeling relation.

3.2. Simple models

Now consider the canonical modeling relation as shown in Fig. 4 (Rosen, 1991; Cariani, 1998). As with the control relation, the processes of the world are still represented to the system only in virtue of measurement processes. But now the decision relation is replaced by a prediction relation, whose responsibility is to produce a new representation which is hypothesized to be equivalent (in some sense) to some future observed state of the world. To be a good model, the overall diagram must commute, so that this equivalence is maintained.

As with the control system, this is a functional representation, and a structural version is also possible in Fig. 5. Here as well the sensors enter into relations with states of affairs in the world and create representations, but these are now sent only to a comparator. There is no relation back from the system to the world.

4. Complex control

Of course, all of the relations described above in Section 3 are a great deal more complex in real control systems. Building from the simple control systems and models, we can identify a number of more complex cases.

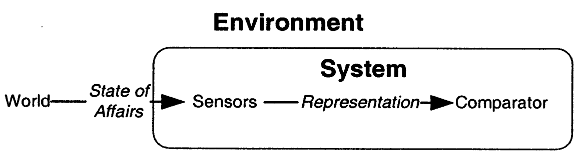

Fig. 5. Structural view of the modeling relation.

4.1. Computation in control

In particular, typically much more can be done with the measured representation than simply passing it on to the agent for decision about action. It is possible to augment the control system with a relation between one representation and another, where the representation of the world is acted upon in such a way as to create a new representation. We call this new relation abstractly "computation", as shown in Fig. 6 in both the functional (left) and structural (right) forms.

While using this term, we again wish to equivocate somewhat on finely specifying our sense here. We mean only to imply a process which creates one representation from another. The prediction relation in models, for example, is "computation" in this sense, as we will recognize in Section 5.1 below.

In real systems this "computation" could, in fact, be many things, but stands in the role of cognition, information processing, or knowledge development. It could be the combination of perceptions in neural organisms or the results of a real computation in machines. Typically, extra or external knowledge about the state of the world or the desired state of affairs can be brought to bear, and provided to the agent in some processed form, for example as an error condition or distance from the optimal state. The point is that this second representation is what is passed to the agent for decision.

4.2. Hierarchical control

At this point we have recovered the classical view from linear control systems theory. While familiar to us as a standard engineering discipline (Nise, 1992), it is also being generalized to a number of other engineering (Albus, 1999) and scientific (Meystel, 1996) domains.

In particular, we are impressed by Bill Powers' system for hierarchical control (Powers, 1973, 1989, http://www.ed.uiuc.edu/csg), which he has

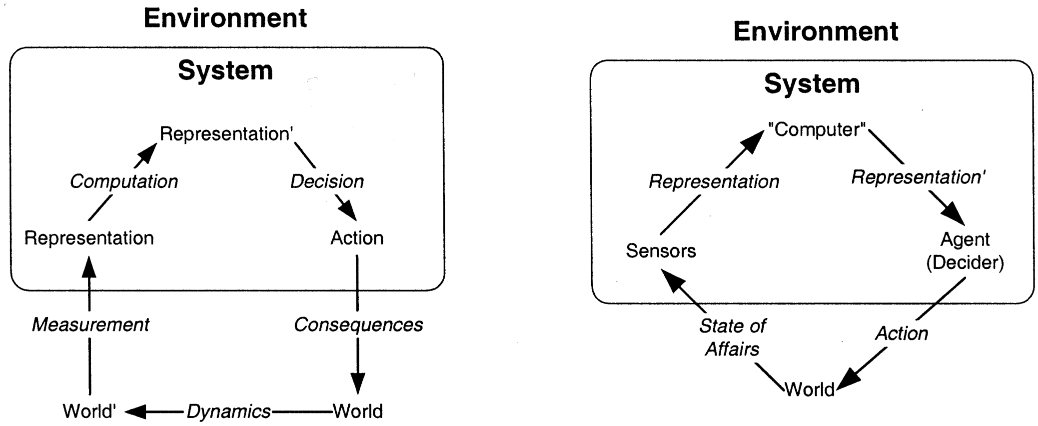

Fig. 6. Control system with computation: (left) functional and (right) structural.

successfully generalized to explain the architecture of neural organisms in general, both as individuals and in social collections. His general scheme is shown in Fig. 7. Note that while this is a structural view, as in Fig. 3 and Fig. 6, we find it somewhat more convenient here to re-use the term "measurement" to refer to the process by which a state-of-affairs of the world produces a representation in the system. This continues throughout our discussion of Powers' theory through Fig. 9.

As shown in Fig. 7, he views the computer as a comparator between the measured state and a hypothetical set-point or reference level (goal). This then sends the second representation of an error signal to the agent. He also explicitly includes reference to the noise or disturbances always present in the environment, against which the control system is acting to maintain good control. For us, these are bundled into the dynamics of the world.

Another great virtue of Powers' control theory model is its hierarchical scalability. Fig. 8 shows such a hierarchical control system, containing an inner level 1 and the outer level 2. The first key move here is to allow representations to be combined to form higher level representations. In the figure S_1 and S_2 are distinct low-level sensors providing low-level representations R_1 and R_2 to the inner and outer levels, respectively. But R_1 is also sent to the higher level S_3, and together they form a new high-level representation R_3.

The second step is the ability for the action of one control system to be the determination of the set-point of another, thus allowing goals to decompose as a hierarchy of subgoals. In the figure, the outer level uses R_3 to generate the action of fixing the set-point of the lower level.

Notice that the overall topology of the control loop is maintained. While ultimately the lower level is responsible for taking action in the world, it is doing so under the control of the comparison of a high-level goal against a high-level representation. Neural organisms especially are systems of

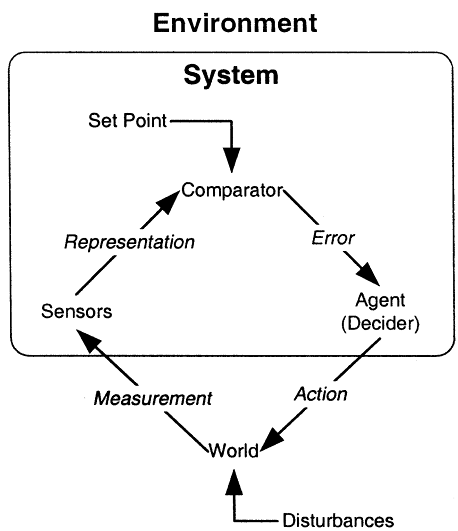

Fig. 7. A Powers' control system.

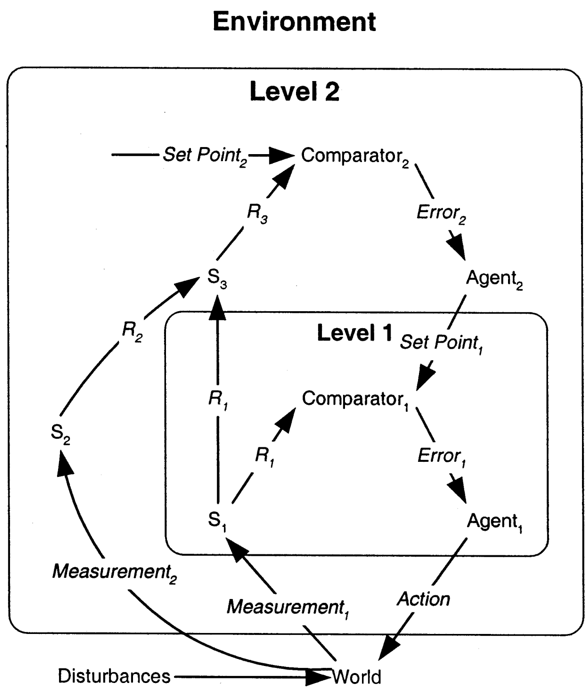

Fig. 8. Hierarchical nesting of Powers' control systems.

this type, low-level motor and perceptual systems combining to accomplish very high-level tasks. And of course, determination of the outermost goal cannot be included within Powers' formal model.

While Powers' theory is cast first in terms of individual control systems interacting with their environments, we can extend this to the multi-system case as introduced in Section 2. As shown in Fig. 9, multiple control systems can interact with a single set of controlled variables in the real environment. Thus the actions of the other system provide a portion of the disturbances perceived by the first system. Powers has provided significant insights into the nature of control in complex systems through the development of his concepts of conflict among control systems and skepticism about the possibility of social systems forming an actual control system at their level of analysis.

5. Hybrid modeling and control

As constructed so far, modeling and control are distinct ways in which a system can be related to the world (its environment). Models and control systems are contrasted by their different topological structures. Recalling our usage from Section 2, in the modeling relation, only g from the environment to the system is present as a measurement function, and thus the structure of a model is fundamentally linear, from the world to the model.

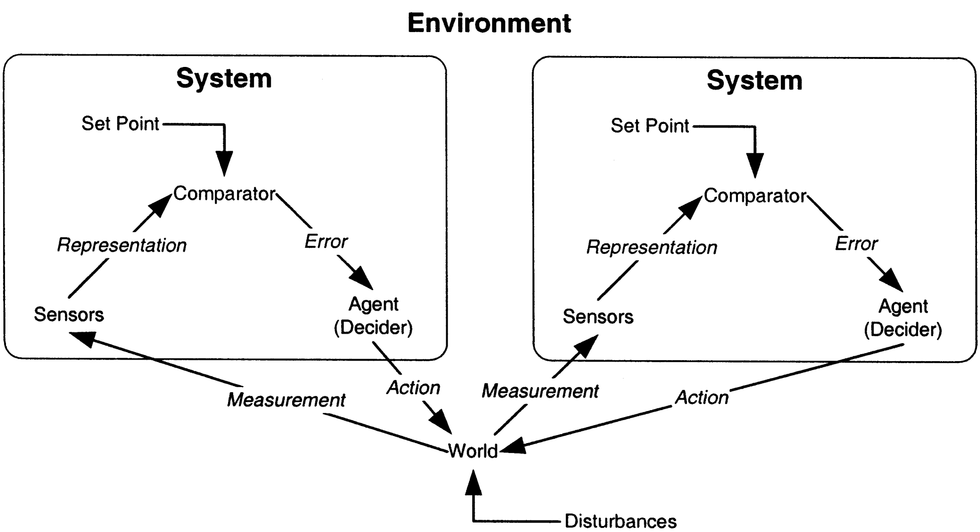

Fig. 9. Social collections of control systems.

But in a control relation, g is present as measurement, but f is also present as the action relation from the system back to the world. The outputs of f are, in fact, connected to the inputs to g through the dynamic processes in the world. Thus control is fundamentally circular, in fact a closure, from the system to the world and back again; while models are fundamentally linear, a throughput from the environment to the system.

So while models and controls are distinct forms of organization, at the same time they share much in common:

- They both hold a measurement relation from the world to the system.
- In both models and controls with computation, there is a relation where one representation is produced from another, namely prediction and computation, respectively.

Yet still the topologies remain distinct, one a circular structure connected to the world, and the other a linear structure from the world to the system. So it is clear that control can be done without computation, modeling, or planning, based strictly on feedback. The difference is that in control the representation of what *is* compared with what is *wanted*, while in modeling it is compared with what is *expected* (based on the model's predictions).

We now wish to consider forms of semiotic organization where both modeling and control occurs together. We assert that such hybrid modeling and control actually represents not only the predominant form of control with which we are familiar, but that it is also frequently held as being the only form of control which could exist or is interesting. We will unpack the foundations of this question in terms of the literature on feedforward, anticipatory, or model-based control.

5.1. Mixed modeling and control

The simplest way to construct a hybrid control and modeling system is shown in Fig. 10. Here we begin with the functional view of control with computation as in the left side of Fig. 6. This is then modified to include a second measurement step, and a comparison between this and the computed representation. This second measurement is used to corroborate the results of the computational step. Note the presence, thereby, of an embedded model, identified by the dashed lines.

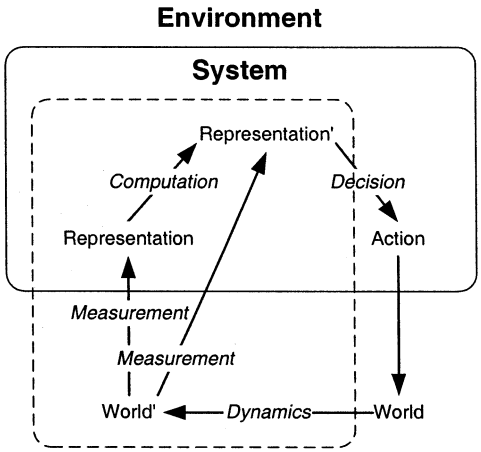

Fig. 10. Simple hybrid modeling and control.

Functionally the roles have become a bit mixed now, since world is the source of both the initial sensory input and the subsequent corroboratory measurement. In fact, these steps are separated in time. Fig. 11 shows both the measurement relations from the world to the system and the action relations from the system back to the world in temporal decomposition. The diagram is actually a bit of a caricature, showing one particular "trajectory" through the space of alternating actions and measurements over time. (Note that we ignore here for convenience the possibility of simultaneity).

The point is that sometimes the system is acting, and at others it is measuring, either to support decisions leading to actions, or for model corroboration. Thus within the diagram we can see the structures of both models and controls. For example, the subsystem enclosed by the dashed lines on the left is a linear modeling relation, while other portions of the diagram reveal embedded circular control relations, albeit temporally decomposed.

Notice also that we can now identify an additional relation, not evident before, directly from the agent to the *representations*. In the structural

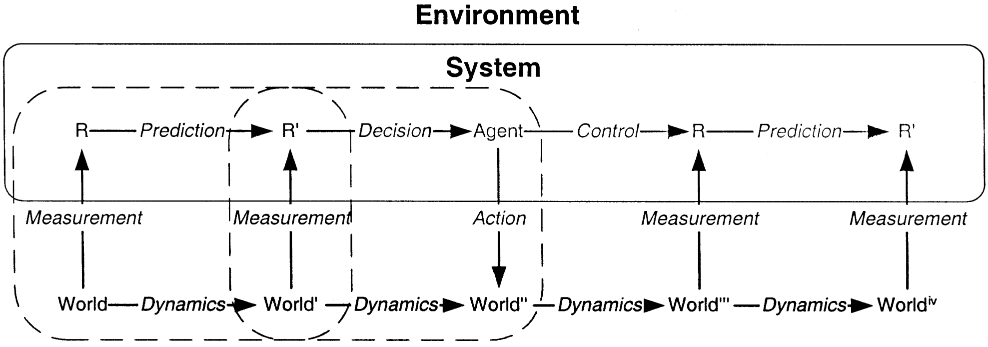

Fig. 11. Temporal decomposition of hybrid control.

view of control, as in Fig. 3, this relation is always mediated through the actions of the agent in the world. But in this temporal decomposition it needs to be identified, and we must ask ourselves which relations the agent manifests on or with the perception.

Here we invoke constructivist maxim of Powers (1973) that it is not, in fact, the state of the world which is being controlled, but rather the *perception* of the state of the world by the system: the system uses variable means to accomplish constant ends, and those ends are in fact the recognition of some form of stability in the environment through some form of constancy in the perceived representation. Thus we recognize this relation as the *control relation itself*.

Finally, we note that Sharov (1992) has also invoked this scheme, in a somewhat more specialized form, as a generalized form of learning.

5.2. Regulation vs. feedback control

As we noted above, some form of hybrid modeling and control has come to dominate most senses of how control is viewed. The difference between control and modeling relations, and even the fact that these need not be present simultaneously, has often been confused in both the systems and semiotic literature. For example, Sebeok implies that modeling requires a control relation:

> Modeling [implies a conception of the world] where the environment stands in reciprocal relationship with some other system, such as the individual organism, a collectivity, a computer, or the like and where its reflection functions as a control of this system's total mode of communication (quoted in Cobley and Jansz, 1999).

But in the classic and highly influential paper "Every Good Regulator of a System Must Be a Model of that System", Conant and Ashby (1970) assert exactly the converse.

Fig. 12 shows Conant and Ashby's scheme of general regulatory control. They establish a system in which a set of disturbances D affects a set of unregulated variables V and a regulatory mechanism R. In turn, R and V jointly affect a set of critical variables Z, and when control is maintained then Z is constrained to a subset $G \subseteq Z$.

But regulation of this sort is a decidedly *linear* mechanism: while R affects Z, there is no necessary relation from Z back to R or V. But R and

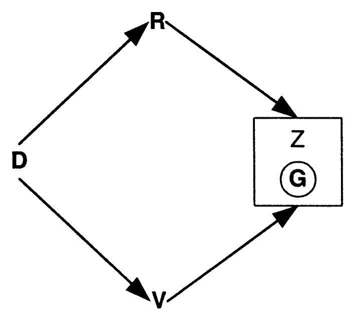

Fig. 12. Conant and Ashby's cause control.

V are seen as tightly coupled. They both receive input from D, and the task of R is to calculate an appropriate compensation, which is combined with the affect of D on V to finally affect Z. This is what Conant and Ashby call *cause control*.

Of course, they do deal with feedback control (Section 5.3), which they call *error control*. But they recognize it *only* as a case of general regulation.

> Regulation by error-control is essentially information conserving, and the entropy of Z cannot fall to zero (there must be some residual variation). When, however, the regulator R draws its information directly from D (the cause of the disturbance) there need be no residual variation: the regulation may, in principle, be made perfect (Conant and Ashby, 1970).

It is true that feedback control (error control) must leave residual variation in Z, depending on band widths and loop gains of the various subsystems. This is the familiar cycling of Z around its optimal state in engineering control systems, as with the thermostat. As the loop gain increases, the measure of the cyclic or chaotic attractor in the controlled variables shrinks, in the limit to a point attractor.

But what is crucial in the quotation is the use of the term "in principle". Perfect cause control is *only* possible if *every* disturbance can be compensated for *exactly*, and in exactly the right time. As the complexity of the environment grows, then by Ashby's (1958) own Law of Requisite Variety the amount of information (structure) necessary in R grows without bound. And with *any* residual error in the regulator R, the overall error of Z can in turn grow without bound.

But feedback control (error control) has no such deficiencies. Because the result of the compensation is actually *observed* by measuring Z directly, any residual error left over from incomplete compensation can be combined with environmental perturbation from D or V, and then "resubmitted" to the control mechanism via the feedback loop. There is never an opportunity for error to grow uncorrected.

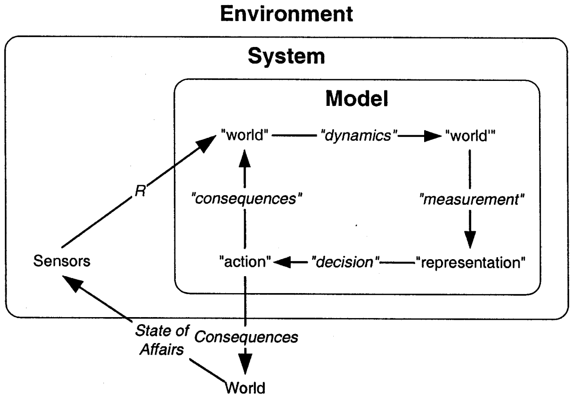

Fig. 13. Anticipatory control using endo-models.

But although such feedback control can be remarkably good, it requires trading off increased model complexity for increased quality of control. The relation between the views of a control system in terms of regulation vs. control is analogous to that between Ptolemic and Copernican astronomy. The earth-centered view is simple and comforting, and can be logically held in principle, but requires an indefinite number of epicycles, or in other words, a model of arbitrarily increasing complexity. But it is the complexity of the *environments* of real world systems which is essentially unbounded. So while *perfect* cause control may be possible *in principle*, it is not *in fact*, nor is it actually *manifested* in real systems such as organisms.

5.3. Anticipatory control

In Section 5.2 we described cause control as involving the prediction of future events to guide actions. We are also familiar with cause control as anticipatory (Rosen, 1985) or feedforward (Klir, 1991) control. Fig. 13 shows a simplified architecture, with an endo-model embedded *within* a control system. It simulates multiple possible "actions", and if the endo-model is stable as a simulated internal *control* system, then that action can be propagated outwards into the "real" world. Thus now if there is a set-point, it enters the endo-model, and is compared not with the perception R (which is used to instantiate the endo-model), but with the final state of world.

It is this view which most dominates our conception of the nature of control in general, arising with cognitive organisms, and predominating, for example, artificial intelligence applications. Frequently this anticipatory perspective is assumed, perhaps implicitly, without even being realized. For example, in Conant and Ashby's architecture R must contain an endo-model in order for it to know which actions to take to limit Z to $G \subseteq Z$. But it is a real question to what extent simpler natural control systems, such as primitive organisms, have internal models at all.

Moreover, this architecture is actually highly complex and special. As shown in Fig. 13, now the agent is replaced by an inner system which is *both* a model and a control system (the external set-point is not shown, and the arrows have been reflected diagonally to make the graph planar and ease the drawing). This inner system is a control system in the sense that there are states of its " world", its "dynamics", and an "agent" making decisions.

However, it is also a model in that the states of its "world" are in fact representations, and its "dynamics" is actually a prediction function. The inner system is totally contained within the outer system, and runs at a much faster time scale in a kind of modeling "imagination". The representation R from the sensors is used to instantiate this model, which takes imaginary actions resulting in imaginary stability within the model. Once this stability is achieved, then that action is exported to the real world.

Note that the outer control loop here is simple, lacking computation. In Powers' terms, there is no set-point which the state of the internal model is being compared to. But this could be present in a slight elaboration where an imaginary measurement is taken from "World" and compared to some set-point. The outer error signal would then be fed to change the imagined actions inside the model until stability is achieved.

6. Controls and models as semiotic systems

No that we have explicated models and control in general, and their interrelation in simple and complex architectures, we move on to consider them in their capacity as semiotic systems.

6.1. Traditional semiotics of modeling and control

Models and control systems are frequently both cast in a semiotic context. We sketch our understanding of a "standard" such characterization here. But first, we now take representations to be symbol tokens: discrete sign-vehicles which have an arbitrary motivation (no necessary shared properties) with respect to the meanings, and exist outside of the temporal scale of the environmental dynamics. We do this primarily for simplicity, recognizing that considering more general iconic or analogical semiotic relations is a more complex, and yet compellingly interesting, situation.

We can then invoke Morris'es distinctions among three distinct classes of semiotic concepts, which following (Cariani, 1989; Deely, 1990) we interpret as:

Syntactic: Concerning the relations (usually formal) among the symbol tokens in a symbol system.

Semantic: Concerning the interpretation of symbols as their meanings.

Pragmatic: Concerning the use of symbol tokens and their meanings for the overall purposes or survivability of the system.

A traditional view of the roles of syntactic and semantic relations (in particular) is shown in Fig. 14. Here the measurement and action functions embody the semantic relations. Together they "ground" the symbols used inside models by connecting them to the world (Harnad, 1990). The syntactic function then becomes the prediction relation which produces one representation from another, or the decision function which produces an action.

6.2. Constraints present in control and modeling relations

However, our view is that this position does not put sufficient restriction on the concept of meaning and semantics, in particular by threatening to "reify" the concept of the *symbol* as *object*, as opposed to the *process of interpretation* by which tokens are *taken for* their meanings. In our view, meaning and semantics can only be present in a system when a decision has been made to interpret a giving token according to one meaning, and not another, in virtue of a coding constraint which has itself been established contingently by selection. In the remainder of this section we will explicate this position.

In Section 3.1, we described how in the functional view of systems, the components represent logical constructs, while the relations represent constraints the components place on each other's range of variation. Here we analyze the relations present in the functional decomposition of control in terms of all three semiotic categories and in terms of the constraints they place on the logical components of the control system.

Measurement: *The constraint placed on tokens by the world.* The production of a token inside the system results from its interaction with the world, by taking an aspect of the continuous dynamics of the world into a discrete, static state outside of that dynamics (Pattee, 1996). In sharp contrast to coding or computation, measurement provides the "grounding" of the symbol tokens. It remains a point of dispute whether measurement is sufficient to provide semantic relations, but it is certainly necessary.

Computation: *The constraint placed on tokens by themselves.* Codings are an expression of syntax, and are usually deterministic. It is essentially string replacement: the presence of one token results in the appearance of another. As Pattee (1997) has commented at length, coding substitutions are computational, memory-dependent, and rate-independent.

Decision: *The constraint placed on actions by tokens.* Given the presence of a certain representation, either as the result of measurement or of computation, a particular action results.

Dynamics: *The constraint placed on the world by itself.* Effectively the rate-dependent dynamical structure of the universe. These are deterministic at *some* level, even if only within the bounds of some structure of uncertainty (for example the probability distribution of a quantum or classical chaotic process).

6.3. Rules as contingent functional entailments

We have cast all of these relations (measurements, computations, decisions, and dynamics) as forms of constraint. And while constraint is a quantitative concept admitting to degrees, in fact in real systems they all have a high degree of constraint, more or less deterministic. The computation and dynamic relations are the traditional paradigms of this form of determinism.

But even measurements are deterministic to the extent that they are reliable and accurate. In other words, given a particular model (a particular set of measurement and prediction relations) or a particular control system (a particular set of measurement, decision, and action relations), there is then very little freedom: a given state of affairs in the world will result in specific representations, predictions, decisions, and actions.

But that is not to say that all these relations are necessarily the same *kind* of constraint. In particular, we can distinguish between the kinds of constraints which Pattee (1982) calls *laws* and *rules*.

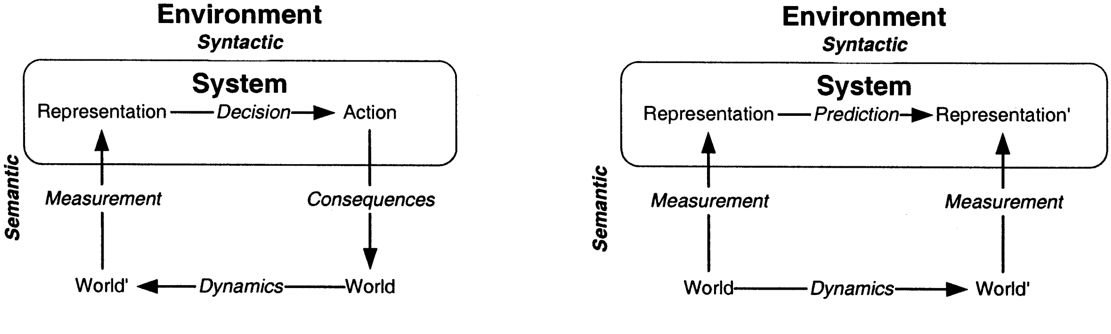

Fig. 14. Traditional understanding of the semiotics of (left) modeling and (right) control.

As explicated by Joslyn (1998), laws are wholly (ontologically) necessary at all levels of analysis, but rules are necessary at one level, and contingent at another: once a particular rule or coding (set of interpretations) is established, then it must be followed, but in general, from a perspective outside the system, many such interpretations are possible.

As an example, in Newtonian mechanics the possible values of F, m, and a are mutually constrained in the relational (Mesarovician) sense that the state space $\mathbb{R}^3$ representing $F \times m \times a$ is restricted to a subset, in fact deterministically to the two-dimensional surface described by $F = ma$. Similarly, the genetic code is a relation in the space {codons} × {amino acids}, in fact a function mapping {codons}$\mapsto${amino acids}. Both of these examples are regularities or associations, which we can characterize as *entailments*. Further, they are deterministic, and thus relationally act as *functional entailments*.

The genetic code, like the coding f in our example above, is one such mapping among a space of possible mappings. Which mapping(s) exist(s) in the world is a contingent fact of history: it could have been otherwise. Thus these are *contingent functional entailments* (Joslyn, 1998), and we call such relations "rules". But in the other example, which surface within $F \times m \times a$ describes the relations which exist in the world is necessary and inexorable. Thus these are *necessary functional entailments*, and we call such relations "laws". So both laws and rules create relational constraints. Returning to the discussion from Section 2, saying that "a law is a constraint" is to say that the action of a law is to constrain phenomena. Any two of F, m, or a necessarily together determine the third, in a lawful manner. However, any other more limited relational constraints, for example among pairs, perhaps created by a rule-like physical constraint e.g. linking m and a alone, does not.

For a more complex example, the position of bumpers on a pool table creates a particular constraint on the possible trajectories of balls. Note that this is a physical constraint which is acting as a rule, since the bumper positions are contingent. In fact, both the bumper positions and the walls of the table act as rules, since they are contingent functional entailments, while physics acts as the law, since it is a necessary functional entailment. Nevertheless, all three create distinct *relational* constraints, in that they limit the trajectories of the balls. In that sense, the law is physically constrained by the bumper positions, and is simultaneously itself a *relational* (not a *physical*) constraint.

Rules are *dually* contingent and necessary at *complementary* levels of analysis. From *within* the symbol system, the token must necessarily be interpreted according to the code, but from *without* we are (or "evolution is") free to choose any coding we please. This property of the conventionality (Lewis, 1969) of rules is the hallmark of semiotic systems. Indeed, rules in this sense thereby capture the Peircean sense of "habit", the de Saussurean sense of the arbitrariness of the sign-function, Jakobson's distinction between symbols and other iconic or indexical signs, and Eco's (1979) use of the concept of "motivation" to describe the amount of properties shared between token and referent.

This combination of freedom and determinism is not possible with purely physical systems. Indeed, the school of biosemiotics (Hoffmeyer, 1996) is dedicated, in some sense, to the proposition that the classes of semiotic systems and living systems are equivalent, or at least coextensive (Deely, 1992; Joslyn, 1998). In the example from Section 3, there is no fundamental natural law of the universe which requires f to be selected according to the principles of negative feedback. Instead, this selection is *contingent on*, and *results from*, the process by which the system is *constructed*.

6.4. Selection as constraint of rules

So given a particular relational constraint, whether from a rule or a law, we can also consider the possibilities for that constraint itself to vary. We noted this in the possibility of multiple f in the organism example from Section 3.1, and multiple potential genetic codes or perhaps we can move the bumpers around on the table. The walls of the table then provide the limits of that variability.

But considering again $F = ma$ as a relational constraint (a two-dimensional surface in $F \times m \times a$), at a *different* level of analysis we can consider the possibility that a different surface within $F \times m \times a$ might describe the relations among F, m, and a. Since this is not possible in this universe, we recognize $F = ma$ as a law.

This complex complementarity of levels of freedom, of variations of constraints, is precisely the hallmark of semantic relation, in that it is the making of *appropriate* choices (relative, ultimately, to an organism's ability to persist or survive) which is the semantic function in a semiotic system. It is on this required "appropriateness" of the choice of the agent that the "intelligence" of the semiotic system rests: a certain action is "correct" in a given context, while another is not. It is only on this basis that meaning or semantics can be said to be present in a control system or a model.

Thus the presence of rules (contingent functional entailments) in a "good" system, whether an "accurate" model or a "good" control system, implies a level of *meta-constraint* in addition to those identified in Section 6.2, namely the constraint on which *rules themselves* are viable. In the example from Section 3, this constraint can actually be measured information theoretically as $\log_2(27/3) = 3.17$ bits.

This additional level of constraint is what Pattee (1997) calls *selection*.

Selection: *The constraint on measurement, computation, and decision relations by the world.* This new level of constraint is the constraint within the space of all possible rules, in particular of all possible measurements, all possible computations, and all possible actions.

Selection is an example of the *pragmatic* aspect of semiotic systems, and must be provided by a force acting outside of the system (control system or model) itself. The typical agents of this constraint are either natural selection or the decisions provided by designers.

Thus in a system which has contingent functional entailments (rules) the pragmatics of the selection of those rules invokes semantic relations of meaning among the components. In our example, it is appropriate to say that for our organism "too hot" actually *means* "go down", and "too cold" actually means "go up". This meaning is present in virtue of the *action* of interpretation provided by the agent. It is the agent which, by manifesting the coding relation f, takes "too hot" to mean "go down".

7. Conclusion: towards meta-system transitions and semiotic closures in social systems

We wish to close with a few points. First, we have explicated models and controls as systems of interacting constraints, and semantic relations within them as rule-like potential "variations of constraints". Going one level further invokes the possibility that this variation of constraint can itself be constrained. This concept of "constrained variation of constraint" is the definition Heylighen (1995) provides of the "meta-system transition", itself offered originally by Turchin (1977) as the canonical process of creation of higher levels of control in complex evolutionary systems. We are especially pleased to see the intersection of this detailed analysis of semiotic systems with the grand cybernetic evolutionary theories of both Powers and Turchin.

Then, where does the above analysis leave us with respect to Pattee's concept of semantic or semiotic closure in particular? A simple-minded parsing would say that any control system is, in fact, a semiotic closure, since it is a semiotic system manifesting semantic and pragmatic relations through circular, closure, relations with its environment.

But this is not satisfactory, since clearly Pattee is trying to express this concept of closure at another level entirely, namely that at the level of selection, or the pragmatic constraint placed on the selection of the measurement, computation, and decision relations themselves. Unlike the clear distinction between system and environment, semantic or semiotic closure expresses the view that the interpreting agent is in fact itself a *referent* of the semiotic system. Further, the actions that are taken into the environment as a result of the interpretation of measured tokens can themselves affect those coding relations, for example by constructing another system (organism) capable itself of manifesting the same semiotic relations.

So finally, as the discussion moves to consider multiple semiotic systems, here across generational time, for our final point we would like to refer back to the discussion from Section 4.2 concerning multiple interacting control systems. Above we considered complex control in the sense of "deep" control involving multiple levels of representation or modeling. Ultimately we are interested in considering complex control in the "broad" sense of control among multiple interacting control systems or in complex environments.

As a paradigm, consider the possibility of a form of "social control", where a community of multiple, independent, interacting control systems form a higher level aggregated control meta-system. This is the situation considered at length by Turchin (1977) and called a "meta-system transition", and has been considered by Powers (1973) as conflict situations among multiple control systems.

Even the simplest such two-element social control system is quite complex, and its analysis is beyond the scope of this paper. Consider, for example, that for each of the component control systems, not only is the reference level (set-point) of the other available to it, but in principle the entire other control system is part of its environment. Powers has commented at length on the failure of one control system to be ever able to *truly* control the other in his formal sense, and has suggested that the entire concept of a social control system is invalid.

If control is truly possible among a community of systems, the challenge will be to identify the key components necessary for any control system, in particular the measurement function and reference level. That is, where are the *representations*, where is the *semantics*, at the social level, as distinct from the iterated semantics of the constituent systems? And ultimately, what is the possible nature of *selection*, the source of all meaning, at the social level?

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