

Elastic Systems: Role of Models and Control

Heikki Hyötyniemi*

*Helsinki University of Technology
Control Engineering Laboratory
P.O. Box 5500, FIN-02015 TKK, Finland

Abstract

Neocybernetics, and specially the framework of elastic systems, gives concrete tools for formulating intuitions concerning complex systems. It can be claimed that a cybernetic system constructs a *model of its environment*, and it applies *model-based control* to eliminate variation in its environment. There exist various valuable control intuitions that are available for understanding cybernetic behaviors, including experiences with *adaptive control*. It turns out that even the evolutionary processes making the systems more and more complex are *thermodynamically consistent* when seen in the control perspective.

1 Introduction

It seems that artificial intelligence is returning to its roots: It used to be cybernetics, as proposed by Norbert Wiener that was one of the cornerstones of early AI, and, still, the same ideas hold. The original reason for intelligence is not to do fancy reasoning, but to survive, and to constitute a functional whole in its environment.

Behaviors in cybernetic systems are based on interactions among low-level system components, constituting structures of *feedback*. In another perspective, feedbacks can be seen as *control*. This understanding has been exploited, and, indeed, cybernetics has also been defined as being study of *communication and control in an abstract sense*. The claim here is that the framework of neocybernetics makes it possible to make the abstract intuitions about communication and control concrete and analyzable.

Since the introduction of cybernetics back in 1950's, control theory, or, more generally *system theory* has matured. Whereas there was plenty to explore in traditional control structures during the last decades, it seems that by now the easy intuitions have been exhausted. The limits of the control paradigm are now visible, and it is evident that there are problems.

It needs to be recognized that control theory is not in all respects an appropriate framework to understand natural complex systems: The main counterargument is that control practices are based on extremely reductionistic approaches and centrally operating control structures. The real cybernetic popula-

tions — economies, ecologies, etc. — are based on distributed operations, and it is difficult to see how the centralized structures could be relaxed and reorganized.

Getting distributed by definition means loosening the controls, and major shifts in thinking are needed in engineering and AI. Indeed, traditional centralized control is a prototype of Western ways of structuring and mastering the world — but when applied in modeling of complex systems, there is the unpleasant feel of finalism and purpose-orientedness in the models¹.

There is a two-way contribution here: Control theory gives powerful tools to understand complex systems, but, at the same time, neocybernetic models may give fresh perspectives to the control community. Today, one cannot even imagine the approaches that someday perhaps become possible what comes to distributed agents and complex networks.

What is more, even the most fundamental notions of system theory are challenged by cybernetic considerations. Before having some *function*, a complex system intuitively does not deserve to be called a system. Whereas in system theory there are some crucial concepts, like the distinction between the inside of the system and the outside environment, in cybernetic systems such boundaries become blurred, the environment equally reacting to the system. A system could be defined not as being characterized by some formal structures, etc. — a system is a *functionally complete sustainable entity*.

¹Perhaps because of the monoteistic view of natural order, one searches for the underlying *primum movens* — Jean-Paul Sartre has said that *even the most radical irreligiousness is Christian Atheism*

2 Cybernetics as control

New useful intuitions can be reached when the contents of familiar concepts are “refilled” with fresh semantics. When studying complex systems, control engineering seems to offer just the right connotations.

2.1 Information vs. noise

Ross Ashby coined the *Law of Requisite Variety* in 1952:

The amount of appropriate selection that can be performed is limited by the amount of information available.

This is a deep observation. The concept of *information* is, however, left somewhat vague here, and the consequences remain obscure. To make it possible to efficiently apply mathematical tools, such basic concepts necessarily have to be defined in an accurate manner. How is information manifested in data?

When looking at the neocybernetic models in (Hyötyniemi, 2006a), one can see how the models see the data: When studied closer, it turns out that the weighting matrix in the pattern matching cost criterion becomes

$$W = E\{\Delta u \Delta u^T\}. \quad (1)$$

This means that data is weighted by the correlation matrix when evaluating matches among patterns: The neocybernetic system must see information in variation. Traditionally, when doing parameter fitting applying maximum likelihood criteria for Gaussian data, the approach is opposite — variation is interpreted as something to be avoided — and the weighting matrix is the *inverse* of (1).

When applying Shannons information theory, or Kolmogorov / Chaitin (algorithmic) information theory, the definition of information is strictly syntactical. There is no domain area semantics involved, and thus extreme universality is reached. However, some paradoxes remain: What you expect, contains no information, and *noise* has the highest information content. When applying the neocybernetic view of information, semantics (in a narrow, formalized way) is included in manipulations, making the analyses non-universal — but there is universality among all cybernetic systems. This semantics is based not only on correlations, but on *balanced tensions* among variables. What is expected, is the most characteristic to the system; uncorrelated noise has no relevance whatsoever.

The neocybernetic models are fundamentally based on correlation matrices — principal subspace analysis is just a way of formally rewriting and re-distributing this correlation information. The correlation matrices contain atoms of information, entries $E\{\bar{x}_i \bar{u}_j\}$ revealing cumulated (co)variations among variables. Covariances and variances — such measures for information are easily expressed and exploited, and they are also the basis of modern identification and minimum-variance approaches in control engineering.

2.2 Model-based control

It turns out that a cybernetic system is a “mirror” of its environment, optimally capturing the information there is available. This is not merely a metaphor — note that the formulas in the neocybernetic model (see Hyötyniemi (2006a)) can be given very concrete interpretations:

- **Model.** It turns out that the neocybernetic strategy constructs the *best possible* (in the quadratic sense) description of the environment by capturing the information (covariation) in the environmental data in the mathematically optimal principal subspace based latent variables

$$\bar{x} = (E\{\bar{x}\bar{x}^T\})^{-1} E\{\bar{x}\Delta u^T\} \Delta u. \quad (2)$$

- **Estimate.** It turns out that the neocybernetic strategy constructs the *best possible* (in the quadratic sense) estimate of the environment state by mapping the lower-dimensional latent variable vector onto environment applying the mathematically optimal least-squares regression fitting

$$\hat{u} = E\{\bar{x}\Delta u^T\}^T (E\{\bar{x}\bar{x}^T\})^{-1} \bar{x}. \quad (3)$$

- **Control.** It turns out that the neocybernetic strategy integrates modeling and estimation to maximally eliminate variation in the environment:

$$\tilde{u} = u - \hat{u} \quad (4)$$

The issue of modeling Δu rather than u directly is studied in Sec. 3.1 (when q increases, u and Δu approach each other what comes to the n most significant eigenvalues). Note that in the case of “intelligent agents” that are capable of explicitly taking the competition into account, so that explicit feedback is constructed, original u rather than Δu can directly be modeled.

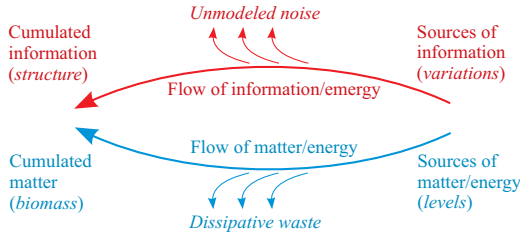


Figure 1: Abstract flows in a cybernetic system

This all means that a cybernetic system implements *model-based control* of its environment. In terms of information as defined above, this control is the *best possible*. The implemented control is far from trivial: It constitutes a multivariate controller where the n most significant variation directions are equalized (or nullified). It needs to be emphasized that the presented control scheme is just an emergent phenomenon, as there are no centralized control units or “master minds”, but everything is based on the local, mindless agents that know nothing about the “big picture”. The symmetric structure of the modeling / estimation loop reminds of Heraclitus’ words: “The way up and the way down is the same”.

2.3 Flows of information and matter

The feedback part in the closed-loop structure above is only an abstraction: It does not correspond to some separate real processes because it only represents the non-ideality of the information transfer. It is interesting to note that for the closed loop structure to emerge, two different kinds of processes need to cooperate — first there is the information flow into the model, and then there is the material flow dictated by the model. Without the other flow the other could not exist either. One could say that a cybernetic system constitutes a *marriage mind and matter*, combining these two incompatible dualistic viewpoints (see Fig. 1).

In the figure, there are the two flows shown separately: On top, there is the flow of information (or energy), and on bottom, there is the flow of matter (and energy). Most of the flows are wasted — in information flow, the uncorrelated noise becomes filtered, whereas in material flow, it is the dissipative losses that do not get through into the higher-level system. Note that it is often assumed that it is these dissipative flows that are the manifestation of com-

plex system dynamics (Prigogine, 1997) — now these are just a side effect. It is the information in the environment (or *variations* in the data) that dictates the structures within the higher-level system, whereas it is the matter (or actual *levels* in the data) that cumulate as some kind of biomass within this predestinated structure of some kind of *niches*. One could even say that the cybernetic model to some extent captures the Platonic *idea* beyond the changing world.

2.4 Hunger for information

A cybernetic system sees information (energy) as *resources* available in the environment. In other words, variation is the “nourishment” for systems, and being capable of exploiting these resources is a prerequisite of surviving in an environment. That is why, it seems that evolutionary surviving systems are “hungry” for more and more information. Again, this sounds teleological — but if some system applies this strategy by accident, it immediately has evolutionary benefit in terms of increasing resources. There is no guiding hand needed — but it is like with Gaia: Even though all behaviors can be reduced to lower levels, simplest models are found if stronger emergent-level assumptions are applied.

It turns out that this eternal hunger has resulted in very ingenious-looking solutions for reaching more information, and, to achieve such sophistication, the systems have typically become ever more complicated. First, the variable values visible in the environment can be actively changed by the system: When an organism develops the ability to move, changing ones environment also changes the variable values. Second, there exist an infinity of environmental variables to choose from, and with enough ingenuity, the resource vector can be augmented in different ways, or the environment can be seen in new ways. To illustrate this, see Fig. 2 — there it is shown how the information content of a signal can reside in different frequency regions. The mathematically compact definition of information as being interpreted as variance makes it possible to exploit frequency-domain methods for analysis. Assume that the system concentrates on band-limited signals, so that the signals are filtered as

$$\frac{du_s}{dt} = -\mu_s u_s + \mu_s u_{in}, \quad (5)$$

and, similarly, there is an exponential “forgetting horizon” what comes to the covariance estimates:

$$\frac{d\hat{E}\{\bar{x}_s u_s^T\}}{dt} = -\gamma_s \hat{E}\{\bar{x}_s u_s^T\} + \gamma_s \bar{x}_s u_s^T. \quad (6)$$

The parameters μ_s and λ_s are filtering coefficients. Then it turns out that only variation in the darkest area in the figure becomes cumulated in the model (or in the covariance matrix), whereas higher-frequency signals are only filtered by the system. Too high frequencies are invisible altogether to the current system, leaving there room for other systems to flourish. As the world gets older, even slower-scale behaviors become statistically modellable — meaning that there is room for ever increasing number of coexisting systems.

The systems are hungry, but they are not greedy. Whereas a system exhausts variation in its environment, there is the same variation inherited in the system itself (remember that PCA model maximally relays variation to latent variables). This gives rise to a *cascade* of trophic layers: Another system can start exploiting the variation that is now visible in the prior system. When the next trophic layer has been established, there is room for a yet higher trophic layer, etc. This kind of succession of systems can be represented as a sequence of “ideal mixers” of information. When new layers are introduced, the ecosystem becomes more and more continuous and smooth – becoming a partial differential equation (parabolic PDE) diffusion model filtering the incoming variation. All loose information seems to give rise to new systems.

Heraclitus said that the underlying principle in nature is *fire* — in the cybernetic perspective, it is this fire that is the driving force, but it seems that the goals of nature could best be explained in terms of a *fire extinguisher*.

There are the physical (chaotic) processes (planets orbiting and rotating, followed by climatological phenomena, etc.) that shuffle the originally “non-informative” flow of solar energy, originally generating the information for other systems to exploit. The input variables on the lowest level are temperatures, nutrients in the soil, diseases, rainfall, etc., and on the level of herbivores, it is then the spectrum of plants to forage on.

The higher-level systems can appear in very different phenospheres, starting from very concrete systems and ending in very abstract memetic ones (see Fig. 3). The interpretation of signals changes from concrete resources to available/required functionalities, and explicit formulations become impossible. For example, take *politics* — also there exist interesting possibilities for applying the cybernetic thinking.

Why democracy seems to prosper even though it is less efficient than a dictatorship? Assuming that there is complete information available in the society, democ-

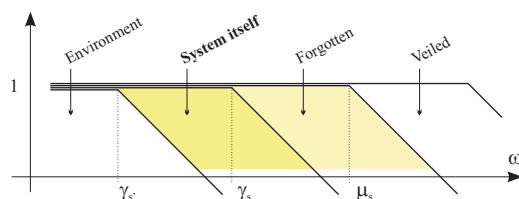


Figure 2: Different systems concentrate on different time scales, seeing the environment in different ways

racy represents the *most cybernetic political system*, information on the bottom (needs of citizens) being maximally transferred to the top (decision makers). Parties determine profiles of opinions; party popularity (number of votes x_i) reflects needs u_j in the society, and this is reflected in its possibilities of implementing party visions.

2.5 Towards optimum?

In cybernetic systems the critical resource is information. In human-made “constructivistic” systems (technical, scientific, ...), the same principle seems to apply, but the variables are more difficult to quantify; the critical resource can be said to be *knowledge*, and one is always “at the edge of understanding”. As soon as there is some new understanding about relationships among variables, it is exploited — this becomes manifested in industrial plants, for example, where new controls are introduced to make the system remain better in balance. These developments are implemented by humans, but, after all, the system follows its own evolution where individual human signal carriers have little to say.

Complex systems seem to develop towards becoming more and more cybernetic. Regardless of the domain, the limiting factor in this evolutionary process seems to be related to extracting and exploiting information (or knowledge). Typical examples are found in working life. The other prerequisite for “cybernetization” — better understanding of the system and gaining more information — is implemented through supervision, questionnaires, and more paper work in general, and the other — applying more efficient controls based on the acquired information — is implemented through increasing administration, organizational changes, missions and visions, and even “developmental discussions”. This is all good, isn’t it?

Unfortunately, the same efficiency pursuit has also come to universities. The role of science is to question and find alternative explanations, avoiding fixed

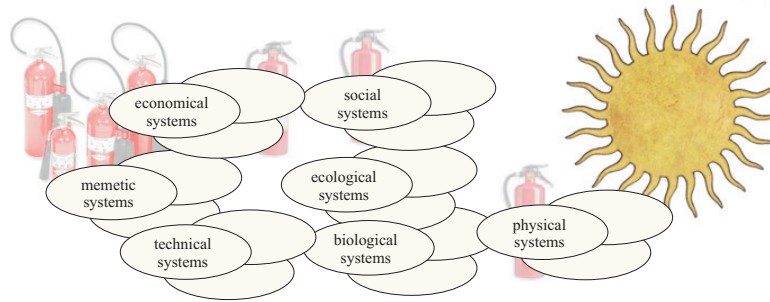


Figure 3: Systems in different phenospheres try to extinguish the Heraclitus' fire

frameworks and controls. This is, of course, far from being efficient, and cybernetization is going on. Whereas the scientific problems being studied are — by definition — missing compact representation, different kinds of variables are needed to make research work better quantifiable. This means that deep problems have to be trivialized, and new measures for “good research” are defined. Earlier the scientific work was evaluated in terms of how well the observed phenomena can be described, but nowadays it is the concrete practical value that is assessed. The traditional ideal in scientific work was self-organization and low hierarchies, but now one is getting back towards hierarchies.

3 Control intuitions

When the control notions are employed, there are many intuitions directly available concerning the behaviors in cybernetic systems. For example, the control system can become *too* good.

3.1 Adaptive control

Adaptation is the key property in truly cybernetic systems, meaning that they are *adaptive control systems*, trying to implement more efficient controls based on simultaneous observations of their environments. If one has control engineering background, one can understand what happens in a truly cybernetic system: Adaptive controllers are notorious in control engineering, as they can behave in pathological ways. The reason for the “explosions” is *loss of excitation*. Good control eliminates variation in data — and after this there is no information where the model tuning can be based on, and gradually the model becomes corrupted. After that, when the model is no more accurate, the variation cannot all be eliminated,

and there will exist information in observations once again. The model starts getting better, and after that the control gets better, and the cycle of good and bad closed-loop behavior starts again; the collapses in control performance can be quite catastrophic. This kind of behavior is typical in loops of simultaneous model identification and model-based control. This result is paradoxical: Good balance on the lower level results in high-level instability.

In complex cybernetic systems, the model adaptations can be more complex than in typical adaptive controls. For example, the sampling rate can become fast as compared to the system dynamics (compare to “quartal capitalism” in economy), but increase in sensitivity in any case follows. The evolutionarily surviving systems are on the edge of chaos where variation is no more information but only noise.

Extreme optimization results in “stiffness” of the system, and worsened fitness in changing conditions. It is again easy to see connections — compare to ancient empires: It seems to be so that there is a life-span for all cultures, after which even the strongest civilization collapses. For example, during Pax Romana, there were no enemies, and the army was gradually ruined — and there was a collapse after a severe disturbance². And this does not only apply to human societies: For some reason, massive extinctions seem to take place in 62 million year cycles (Rohde and Muller, 2005). Do you need some meteors to explain extinctions — or is this simply because of evolution dynamics?

However, as it turns out, the cybernetic strategy where the feedback is implemented implicitly through the environment, results in “gentle” adaptive control, form of *buffering*, where the variation is not

²But explicit emphasis on the army results in the Soviet-type collapse: If there is no real need at some time, such investments are cybernetically non-optimal, meaning that the system cannot outperform its competitors in other fields in the evolutionary struggle

fully eliminated, and the closed loop behavior does not become pathological. This is because it is Δu rather than the estimate u itself that is being eliminated from the input data, and some level of excitation remains, making the overall system evolutionarily stable and sustainable.

However, being too ambitious, implementing extreme optimization, and full exploiting the information completely wiping out excitation, is also a possible scenario in a cybernetic system. This happens if the agents are “too smart”, implementing the feedbacks explicitly. An agent can not only see the resources but also the competitors and take their actions into account — implementation of such explicit feedback results in combined Hebbian/anti-Hebbian learning (see Hyötyniemi (2006b)).

3.2 Inverting the arrow of entropy

The second law of thermodynamics states that in a closed system entropy always increases (or remains the same if the system is reversible). This means that the the system goes finally towards “heat death”, the state of maximum probability, where all variations are eliminated. All physical systems fulfill this principle. However, it can be claimed that cybernetic systems are *thermodynamically inconsistent* as it seems that they operate *against the arrow of entropy*: As new structures emerge, the probability decreases. This difference between “normal” physical systems and “abnormal” cybernetic ones causes an uneasy feeling: Even though there are no outright contradiction here (the cybernetic domain is not closed), different laws apply, and it seems that there must exist different sciences for evolutionary systems.

In the neocybernetic framework, this paradox seems to vanish altogether. Remember that the target of entropy is heat death where everything is in balance — but it was balances that were asumed to be the goal of the neocybernetic systems, too. When the boundaries between the system and its environment are set appropriately, it turns out that *all processes go towards entropy increase*, including the evolutionary ones. There is a minor decrease in the overall entropy when the model of the environment is constructed off-line, once-for-all, but thanks to this model there is huge ever-lasting increase in entropy caused by the on-line variation suppression due to the model-based control. When the environment is seen as residing *inside* the higher-level control system, it turns out that at all levels maximization of entropy takes place. Such observations perhaps offer tools for modeling principles: If it is assumed that all systems go

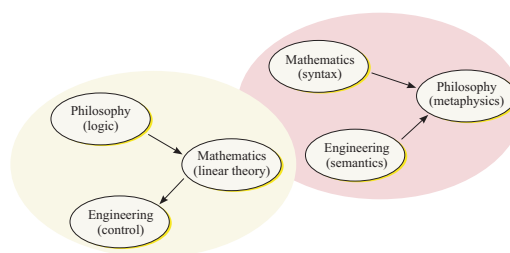


Figure 4: Hierarchy of disciplines. Traditional view, on the left, sees engineering as simple application of the fine theories; the new view, on the right, sees control engineering as delivering substance to philosophies

towards entropy *as fast as possible*, an extremely efficient conceptual framework is available (this principle could be called “maximum entropy pursuit”).

The inversion of the arrow of entropy makes it possible to attack many mysterious phenomena where it seems that improbability cumulates beyond all limits — in the new perspective, such cumulation is no more a paradox. For example, the challenge of *origin of life* can be attacked. The essence of understanding the life processes is, again, in the functions; semantics of life is buried in the notorious concept of *elan vital*. In the neocybernetic setting, such finalistic arguments become issues of entropy production.

3.3 Rehabilitation of engineering

Since 1960’s, after the great discoveries of modern control theory, there have been no real breakthroughs in the branch of control engineering. It seems that this stagnation does not need to last long: There is a Golden Age of control engineering ahead. Control theory and tools can be applied not only in technical applications, but also in understanding really complex system — biological, social, economical, etc. There do not necessarily exist explicit controls in such systems, but understanding the natural dynamics in such systems is still based on control intuitions.

It is traditionally thought that philosophy is the basis of all science: Logic is part of philosophy determining the rules of sound thinking. Mathematics if “applied logic”, implementing the logical structures and manipulating them according to the logical rules. Natural sciences, on the other hand, can be seen as “applied mathematics”, where the ready-to-use mathematical formulas are exploited to construct models. Finally, the engineering disciplines are “applied science”. Engineering is inferior to the more fundamental ways of structuring the world.

This is a formal view of how deductive science is done, how new truths are derived. However, also these viewpoints need to be reconsidered: If the presented neocybernetic modeling can cast some light onto the mysteries of what is the essence of complex systems, the deepest of the philosophical branches, *metaphysics*, is addressed. It is mathematics that offers the *syntax* for discussing the issues of what is there beyond the observed reality, and it is control engineering that offers the *semantics* into such discussions. It can be claimed that control knowledge is necessary for understanding complex systems, natural or artificial (see Fig. 4), involving intelligent ones.

4 Mastering the environment

The whole cybernetic machinery can be studied in the framework of control and entropy maximization. The feedback needs not be implemented in such an implicit way as in the prototypical cases of “static control”, where time axis is abstracted away, but the control intuition extends to dynamic, transitory cases.

4.1 Artificial reflexes

It is *reflexes* that can be seen as atomary manifestations of intelligence, representing reasonable behavior with no brains involved, and automated sensor/motor reactions (conditioned reflexes) can be seen as extensions of that, being learned rather than hard-wired. When variations in the environment are interpreted as resources (or threats), low-level intelligence means immediate benefit: Reaching towards resources (or away from them) can be seen as control towards zero activation, or “heat death” of the local environment.

To study “artificial reflexes” the originally static model framework needs to be extended to dynamic cases. As the system was previously seen as a mirror of the environment, now it is the controller that implements *current state as a mirror between the past and the future*, and, what is more, an adapted control should implement some kind of *balance between the past and the future*. One needs to have a model not only of the current environment but also of how it can be changed; one has to be capable of *simulation*, or estimation of the future. In the control engineering perspective, one could speak of *model-predictive control* combined with *dead-beat control* (see Åström and Wittenmark (1997)).

Assume that the observation vector u is coded as a “perception” or “mental view” \bar{x} . These variables denote deviations from the nominal reference values, so

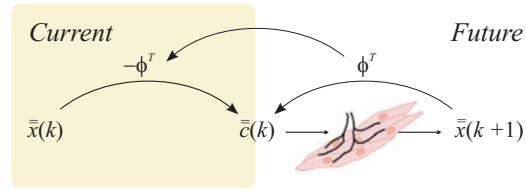


Figure 5: Control as a (antisymmetric) mirror between the past and the future

that in the goal state there should hold $\bar{x} \equiv 0$, meaning extreme loss of variation in the environment. The perceptions are transformed into control signals c that are connected to actuators (muscles). The resulting responses in the environment are then observed and transformed to another set of perceptions. Based on such assumptions, the control scheme in Fig. 5 can be presented. The right-hand side in the figure represents the process of model construction, where the dependencies between the control signal and resulting changes in the observations are recorded, and the left-hand side represents model usage, or on-line construction of the control signals. The model construction is carried out applying the neocybernetic principles for the “input” $\bar{x}(k+1)$ and “latent variable” $\bar{c}(k)$, now assuming that the control and its effects are in balance. The signals with “double bars” are the balance values after the previous-level signals \bar{x} are further exploited as inputs in the control construction process.

The intuitive idea of this control is to make the change in the state *inverse* of the current state, meaning that, when the new state is reconstructed as a sum of the old state and the change, the outcome will be zero state — meaning successful control. The past and the future perceptions are “folded” on top of each other. Whereas adaptation of the actuation model can only take place after the effects are visible, the on-line control construction is strictly causal. Coupling the successive perceptions together implements the trick of collapsing the time structure back to singularity.

The above control scheme is based on a very simple view of the environmental dynamics: The assumption now is that if nothing is done, nothing changes in the observed environment. This makes prediction simple. Yet, the causal structure is no more self-evident, as it is no more physical exhaustion of the variation taking place as a side-effect, feedbacks being explicitly implemented, and control structures have to be explicitly initialized. The minor extension of the assumed environment presupposes that different kinds of extensions are implemented in the basic

neocybernetic model structure. In general, better control means that new structures need to be employed, and there is more need for explicit control of this control.

4.2 From reactivity to proactivity

When looking at truly complex systems, it turns out that the environment itself consists of other systems. When one has a coevolving system of systems, the role of external disturbances becomes smaller and smaller, and it is interaction among subsystems that mainly takes place. When one knows in advance how the environment will react, controls can be designed beforehand. When the subsystems share the same design instructions, changing the environment can turn from reactive to proactive. Indeed, the genetic (memetic) codes are used for bootstrapping the biological (cognitive) systems, activating dynamic attractors one by one, until the final phenotype is reached.

It seems that no matter how sophisticated structures have been developed during evolution, nature has not found the way to put up a running system without repeating the whole sequence. As observed already by Ernst Haeckel, “ontogeny recapitulates phylogeny”.

When a biological system is to be put up in a new organism (or memetic system in another mind), the information can only be stored and transmitted in the form of sequential genetic code (memetic scriptures or spoken tradition). When the environment is favorable, the codes can be interpreted, and the high-dimensional dynamics are started in a hierarchic manner, more complex structures being based on simpler ones, making the system functional and “alive”.

5 Conclusion

In today’s AI, specially in modern robotics, the approaches are typically based on input/output orientation, “intelligent” systems being black boxes, actually in the spirit of the age-old Turing test. Following the developments in cognitive science, perhaps this Brooksian “artificial behaviorism” will someday change to “artificial cognitivism” or constructivism with emphasis on the internal models and model-based control. Neocybernetics is a candidate offering such model structures.

Good control is based on a good model — it is this model that is the key issue assumedly in all cybernetic systems, however abstract they happen to be. The basic idea does not change if the intuitions cannot easily

be turned into concrete numbers. Even all human activities can be interpreted in this framework of finding models and exploiting them for control. For example, scientific activities try to find models for the world — and technology is thereafter employed to exploit this understanding and exhaust the new resources, thus bringing the resource variations to zero.

Arthur Schopenhauer once said that *art* is the only field of human activity that is free of struggle, aesthetic experience making it possible to temporarily escape the “rat-race”. In the cybernetic setting, this activity, too, is in line with other goal-directed activities: If art helps to see the world in new perspectives, it makes it possible to construct alternative models. In all, the purpose of life is to understand the world — to find a model, and then exploit the resources.

Indeed, neocybernetic considerations have close connection to philosophies. Along the lines of Eastern wisdom, neocybernetics emphasizes the role of balances in all kinds of living systems. However, in some sense neocybernetics goes deeper than that: Good life is not only about finding the balance. To find the model, to be capable of identifying the environment, there has to exist enough excitation around that balance. It can be assumed that autoimmune diseases, for example, are caused by an incomplete model caused by absence of natural microbial attacks. Full life is not characterized by loss of challenges; rather, *happiness is one’s knowledge of being capable of coping with any challenge one can face*.

According to Eastern philosophers, the reason for suffering is missing knowledge and understanding — with appropriate models the world and its constituents become a meaningful whole:

Before Zen, men are men and mountains are mountains, but during Zen, the two are confused. After Zen, men are men and mountains are mountains again.

References

- K.J. Åström and B. Wittenmark. *Computer-Controlled Systems*. Prentice Hall, New Jersey, 1997.
- H. Hyötyniemi. *Elastic Systems: Another View at Complexity*. SCAI’06, Helsinki, Finland, 2006a.
- H. Hyötyniemi. *Neocybernetics in Biological Systems*. Helsinki University of Technology, Control Engineering Laboratory, 2006b.
- I. Prigogine. *End of Certainty*. The Free Press, 1997.
- R. Rohde and R. Muller. *Cycles in fossil diversity*. Nature 434, 2005.