NEOCYBERNETIC MODELING AND SIMULATION OF ECOSYSTEMS

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Abstract: When modeling truly complex systems, like ecologies, powerful modeling principles are needed. *Neocybernetics* studies distributed systems where there is no centralized control; *self-regulation* and *self-organization* emerges from local interactions and feedback structures. It turns out that the emergent patterns can be interpreted in terms of multivariate statistical methods: A cybernetic ecosystem carries out *principal subspace analysis* of the resource variations in the environment. The "forage profiles" of individuals together span the directions of environmental variability. Because ecosystem following the neocybernetic adaptation can maximally exploit the resources in the environment, such strategy has evolutionary advantage. Such optimality properties motivate deeper analyses, too.

1. INTRODUCTION

Ecology is said to be "systemic biology" (for example, see (Krebs, 2001)). However, todays population models are still far from capturing the large-scale behaviours in real ecosystems of multiple competing species. Traditional models are built in bottom-up way, single phenomenon (or population) at a time, introducing new functional structures as the model becomes more extensive (for example, see (Turchin, 2003)). As an example of such functional "building blocks", study the growth models for a single species: The starting point being *exponential growth,* more real-life credibility is reached by extending it to a *logistic model,* and further nonlinear fine-tuning factors can be introduced as in the *Monod model,* etc. Each of the structural details adds new parameters in the models.

Similarly, in the prey-predator models, starting from the basic two-species *Lotka-Volterra models,* adding new species means increasing complexity, when each pair of interacting species brings a new coupling parameter in the model. Indeed, the model complexity grows exponentially as its size grows. If such models are made adaptive, careful tuning is needed to reach natural-like behaviors — to avoid explosions, extinctions, and monocultures. To make modeling still more challenging, the available data typically has low quality and high noise level, and there only exist just a few time series to fit the parameters against. One would need strong model structures and conceptual tools to tackle with such challenges.

The basic problem with the current models is that the challenge of *emergence* cannot be addressed in such reductionistic ways: Typically, the models only explain the behaviors that have explicitly been implemented in them. Due to the resulting complexity, the models are difficult to analyze, and because of the nonlinearities, the analyses do not scale up; what is more, the intuitive feel of what is *life* and what is *evolution* are escaping.

When the system becomes very extensive, it would be tempting to start from the other end, looking at the whole system at a time. Interactions within the system can be seen not as a problem but as a resource: Non-trivial functionalities, like self-regulation and self-organization can be implemented in terms of feedback structures among the high number of coexisting populations or individuals. It seems that there now truly exist conceptual tools available to attack the challenge of "systemic ecology".

In this paper, the *neocybernetic model structures* and their properties are studied. This paper summarizes the observations in (Hyötyniemi, 2006); more thorough analyses are found therein.

2. NEOCYBERNETICS

The term *cybernetics* was coined by Norbert Wiener in 1948 to mean the common control principles in natural and artificial systems (Wiener, 1948). During the next decades, the potential of contemporary control theory was examined and exploited extensively. However, now it seems that fresh ideas are needed: The centralized control structures cannot explain the behaviors in the most interesting systems consisting of complex networks or distributed agents.

2.1 Elasticity and evolution

As explained in (Hyötyniemi, 2006), neocybernetics is a compromise between reductionistic and holistic approaches: A view from top is applied, but the structures still remain mathematically quantifiable. Structural complexity is substituted with dimensional and functional complexity: Model structures are linear but high-dimensional and dynamic. There are also other key issues — like the ideas of distributedness and environment-orientedness — that can only be mentioned here.

Environment-orientedness means that the system state $\bar{x}$ is directly determined by the observed environment $\bar{u}$, and because of the assumed linearity, there simply holds

$$\bar{x} = \phi^T \bar{u}. \tag{1}$$

Natural systems typically are in dynamic balance; indeed, they are *elastic* so that environmental disturbances can deform the system, but as the tensions vanish, the original equilibrium is restored. This self-regulation property is caused by the non-ideality of the environment: As the visible environment $\bar{u}$ is determined as

$$\bar{u} = u - \Delta u = u - \varphi \bar{x}, \tag{2}$$

the original environment u is balanced by the negative feedback $-\varphi\bar{x}$, meaning that exploitation of environmental signals simultaneously exhausts them.

The added value of the neocybernetic framework comes from the possibility of quantifying *evolution.* Adaptation in the system is local — it is here assumed that the elementary distributed actors are "selfish", each of them individually trying to exhaust the available signals maximally. In its simplest form one can express the emergent outcome of the adaptation in the symmetric form

$$\phi = \varphi = \mathrm{E}\{\bar{x}\bar{u}^T\}^T q, \tag{3}$$

where $\mathrm{E}\{\bar{x}\bar{u}^T\}$ is the (sample) covariance matrix, and q is the coupling parameter determining the experienced *stiffness* of the system. In a wider perspective, it turns out that when this strategy is obeyed, the coupling between the system and the environment is maximized, and the system properties become equalized: After convergence, all eigenvalues of $\mathrm{E}\{\bar{u}\bar{u}^T\}$ equal $1/q$.

Assumptions about the *goals of evolution* offer strong, general modeling principles. The sharing of such domain-independent "semantics" makes it possible to reach global level emergence of structures with no explicit communication among the low-level actors. This self-organization is a somewhat mathematical concept — it becomes manifested as global-level cost criteria, and one has to employ appropriate mathematical tools.

2.2 Mathematical properties

Assuming that the input data vector u is not constant but stochastic and stationary, one can study the dynamic balance also at the level of statistical constructs, or the *second-order balance.* If one defines $\bar{x} = \Phi^T \Delta u$, it turns that there holds

$$\left(\Phi^T \mathrm{E}\left\{\Delta u \Delta u^T\right\} \Phi\right)^3 = \Phi^T \mathrm{E}\left\{\Delta u \Delta u^T\right\}^3 \Phi. \tag{4}$$

The solution for this is non-trivial if the dimension of x (parameter n) is lower that that of u (m); then it can be shown that the mapping matrix Φ converges so that its columns span the *principal subspace* of the covariation in u, meaning that the columns are linear combinations of the most significant eigenvectors of the covariance matrix $\mathrm{E}\{\Delta u \Delta u^T\}$. In principle, the model implements *principal subspace analysis* — however, closer analysis reveals that automatic rotation of the basis vectors takes place so that the result can be called *sparse subspace analysis.* Further, if the scalar q in (3) is substituted with diagonal matrix Q, modes become distinguished, and one has *sparse component analysis.*

Together the principal component basis vectors span a subspace where the input data can be projected with minimum loss of variation (Basilevsky, 1994). The model thus concentrates on the dimensions where there is maximum variation in the data, or where there is maximum freedom. This approach is *opposite* to traditional model structures that concentrate on *constraints* — typically, models are based on formulas that connect variables together: Each equation decreases the range of possible variations among the variables. The problem is that when the system is very complex, there are huge numbers of such constraints and only a few freedoms left in the data. In the spirit of *Ockham's razor,* rather than concentrating on the constraints, it is easier to concentrate on the remaining degrees of freedom. It is along these remaining degrees of freedom where the interesting behaviors, or *emergent functionalities* in the system take place. One does not need to worry about the actual underlying constraints, as long as it can be assumed that they just exist, keeping the system always in balance regardless of the external disturbances.

The freedoms-oriented thinking also gives a firm basis for *ontologies,* as interpreted in the technical way: What is interesting and relevant in the data is what is most visible. Information is manifested in covariation among data items.

2.3 Simulation issues

When simulating the neocybernetic models, there are special challenges. There are two levels of "emergence" — first, when the input u is applied, its final effect is valid only after the signals have converged to $\bar{x}$ and $\bar{u}$. Second, in the statistical perspective, the model is in balance only after the structures have converged to fulfill (4). This all means that the model becomes extremely stiff, as there exist very different eigenvalues so that the time constants are very different (this stiffness is *not* the same thing as stiffness caused by high q).

However, the process is well-behaving and it can be simplified. It is easy to show that (if there is variation in the input data) the dynamics remain stable; what is more, because of the model linearity, the time axes can be collapsed to singularity. For example, in the following Matlab algorithm the neocybernetic adaptation is carried out in an efficient way (for details, see (Hyötyniemi, 2006)).

```
while ~CONVERGENCE
      % Balance of latent variables
    Xbar = U * (inv(eye(n)+Q*Exu*Exu'*Q)*Q*Exu)';
      % Enhance model convergence by nonlinearity
    Xbar = Xbar.*(Xbar>0);
      % Balance of the environmental signals
    Ubar = U - Xbar*Exu;
      % Model adaptation
    Exu = lambda*Exu + (1-lambda)*Xbar'*Ubar/k;
      % Maintaining system activity
    Exx = Xbar'*Xbar/k;
    Q = Q * diag(exp(P*(1-diag(Exx))));
end
```

It is assumed that the data $u(\kappa)$ from different time points $1 \leq \kappa \leq k$ is collected in the matrix $U^T = \big(u(1) \cdots u(k)\big)$, and this same data is employed until the model $\phi^T = Q\mathrm{E}\{\bar{x}\bar{u}^T\}$, or `Q*Exu`, converges. Before adaptation, this data structure is initialized to have random values.

3. APPLICATION TO ECOLOGIES

When modeling some real systems, like populations, it is, in principle, easy to reinterpret the symbols: The vector $\bar{x}$ represents *population sizes,* and $\bar{u}$ is the vector of *available resources* (different types of food and other living conditions). The columns in ϕ can be called *forage profiles,* exploitation conventions corresponding to the populations. But why should the neocybernetic model be preferred as compared to other modeling methodologies?

There can exist many alternative ways to survive in the environment — why should one favor one specific approach? The key point is that *following the neocybernetic model, there is evolutionary advantage.* It turns out that when the coupling with the environment increases, in a system obeying the neocybernetic model *optimality in terms of resource usage is reached.* This means that surviving, succesfully competing natural populations assumedly must have adopted this strategy. In the long run, it is the models that implement the model based on principal components that can best be matched against variations in the resources u (in terms of quadratic variation criteria), resulting in the most efficient exploitation of the resources. And populations with optimal strategies assumedly outperform others in terms of biomass and more probable survival.

It is perhaps hard to believe that the very nonlinear genetic mutations and accomodation processes, etc. — the actual evolution mechanisms in nature — would have anything in common with the smooth formulas above. How could the simplistic model apply? The key observation here is that it is, again, only the dynamic equilibria that are studied, not all possible routes there. Whereas the adaptation processes can be very complicated and varied, the final emergent optimum can be unique in terms of tensions. When concentrating on the balance only, the dimensionality of the problem goes down, making the optimization process feasible.

When applying the neocybernetic model, ecosystem simulations remain stable even though the dynamics looks locally chaotic: The lowest-level adaptation against the resources is fast but still remains bounded; there is vivid dynamics, but no explosions take place. No fine tuning is needed: If there is enough variation in the resources, after system-wide adaptation a balance is found where there is a "niche" for every species — assuming that the input data is "rich" enough. The niches are characterized by the principal subspace dimensions, the forage profiles ϕ_i mapping from the prevailing resource vector $\bar{u}$ to the balance population $\bar{x}_i$. The roles of the species cannot be predicted, only the subspace that is spanned by all of them together is determined by the environment. The key observations concerning the neocybernetic model properties can be summarized:

- **Robustness.** In nature, no catastrophic effects typically take place; even key species are substituted if they become extinct, after a somewhat turbulent period. Using the neocybernetic model, this can be explained in terms of the principal subspace: If the profiles are almost orthogonal, in the spirit of PCA, changes in some of the latent variables are independent of each other, and disturbances do not cumulate. Also because of the principal subspace, the system reacts fast only to *relevant* changes in the environment, whereas sensitivity towards random variations that are not supported by the long-term signal properties are suppressed.
- **Biodiversity.** In nature, there are many competing species, none of them becoming extinct; modeling this phenomenon seems to be extremely difficult. Now, again, this automatically results from the principal subspace nature of the model: As long as there exist various degrees of freedom in input, there is room for different populations. Within species, this also explains why in balance there exists variation in populations as the lesser principal components also exist (compare to the *Hardy-Weinberg law:* "In a large, random-mating population, the proportions of genes tend to remain constant from generation to generation").

Such populations can reside just as well in economies as in ecologies, and, as it turns out, the models are applicable for social structures within populations. When relaxing the variables, also *memetic systems* can be studied as trying to do "pattern matching" in the ideasphere can be studied applying the same intuitions.

4. ROLE OF MODELS

Control engineering intuitions are essential when trying to understand cybernetic systems. There are no explicit control structures on the low level — but as seen in the holistic perspective, cybernetic behaviors can best be interpreted in control terms.

4.1 Model-based control

There are two levels of "flows" in a cybernetic system: First there is the flow of information (or "emergy") that cumulates as structures in the system, as eplained above; second, there is the flow of matter and energy that cumulates as biomass within the predetermined structures. It is not the dissipative flows that are the key issue in living systems — it is the more or less static attractor structures rather than the noisy, vivid dynamics that are the key point.

When analysing the mapping matrix Φ, it turns out that the feedforward part in the closed loop of flows can be expressed as

$$\bar{x} = \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\}\right)^{-1} \mathrm{E}\left\{\bar{x}\Delta u^T\right\} \; \Delta u, \qquad (5)$$

and the feedback part becomes

$$\Delta u = \mathrm{E}\left\{\bar{x}\Delta u^T\right\}^T \left(\mathrm{E}\{\bar{x}\bar{x}^T\}\right)^{-1} \; \bar{x}. \qquad (6)$$

As has been observed, (5) implements extraction of latent variables in terms of principal subspace; the inverse formula (6), on the other hand, implements *least-squares regression mapping* from the latent variables back onto the higher-dimensional data space. It turns out that the neocybernetic strategy constructs the *best possible* decomposition of the input data, and the *best possible* reconstruction of that data in the quadratic sense, or in terms of information capture and transfer. When both of these levels are combined in the closed loop, it turns out that the system implements *best possible* model-based control of the environment in terms of elimination of variation (some details are ignored here).

Speaking of a system constituting a "mirror image" of its environment is not merely a metaphor. Modeling of the system can be changed into analysis of the properties of the environment.

The mathematically compact framework makes it possible to carry out further analyses. For example, studies of *trophic layers* can be carried out: Whereas information is minimized on the lower level (in the environment) because of the cybernetic controller, it is maximized on the higher level — this comes from the fact that variation is maximally inherited by the system (according to the theory of principal components, the total variance captured by the n most significant latent variables is $\sum_{i=1}^{n} \lambda_i$). This means that the variation in the system can be seen as resource by yet another system, thus giving rise to a cascade of systems. The original input variation in terms of precipitation, sunlight, etc., becomes filtered in the succession of systems when one proceeds from plants to herbivores, etc.

As the ecosystem becomes more sophisticated, the environment of a system consisting of other systems, the system boundaries cannot any more be determined unambiguously. The traditional view of looking at systems becomes obsolete, as it is all the systems together that control each other, the ecosystem becoming a "pancausal" structure.

4.2 Tackling with nonlinearity

The starting point in neocybernetic modeling was linearity — however, the real world is nonlinear. Still, the above observations perhaps help to see the more complex cases in a perspective. Perhaps it is so that the same principles can be employed to characterize systems in the nonlinear cases, too. Perhaps it is the pursuit for the best possible control, based on the best possible models, that always applies?

How can a general nonlinear function be modeled? These issues have been studied for a long time, and it seems that the idea of *mixture models* is a powerful concept to represent a multitude of behaviors. There is a "library" of competing submodels, and the best of the submodels is selected in each case. When looking in another perspective, one can speak of *basis functions* that together span the nonlinearity, together determining an "envelope" for the function.

It seems that nature has employed the same strategies for representing the nonlinear environment. All complex ecosystems consist of more or less heterogeneous populations occupying specific locations in the observed data space, each trying to match that local environment. Again, the nature's implementation is completely distributed, and the matching process against the environment is parallel. An individual is a (sub)model, as is the whole (sub)population, filling a niche, or a locker in the environmental manifold. The cybernetic model of the complete ecosystem is a *model of models.* In a converged model the submodels are rather densely located, exhausting the information available in the environment more or less continuously.

The environmental "function" can be extremely complicated, and when presenting it, there is need for structural alternatives, and simultaneously there is need for capability of smooth continuous tuning of model parameters. One needs to have an interplay between qualitative and quantitative building blocks. It seems that the *genetic code* offers the necessary flexibility: The genotype just determines the framework, and it is the dynamic interplay among the system and its environment that determines the outlook of the final phenotype. The genes define the basin of attraction where the final tuning of the model takes place. The Darwinian mechanisms come here to play to exploit the submodels, implementing the adaptation of the population level mixture model, good solutions among submodels being promoted in the mixture. The optimization among the model prototypes is, however, not merely a random search process. The basic structure of an individual is determined by the genes, but within that framework, the familiar neocybernetic adaptation processes assumedly tune the parameters so that it is the best fit with environment that can be achieved within that framework, so that the structures, and thus the underlying gene combinations, can be compared in an objective way. However, the idea of "survival of the fittest" is not so categorical as it is normally thought to be: Best solutions dominate, yes, but the outperformed ones also can survive, making the view of the reality more complete. Indeed, samples far from the mainstream solutions can carry very much valuable information. There are no outliers among the reproducing individuals, all models are valid: If an individual has survived so long, there must be something special about it; it is the whole adolescence that is there to filter out the actual mistakes[1].

As the "personal catastrophes" (deaths of individuals) are non-synchronized, statistical properties of the population do not change abruptly, and the adaptation of the population becomes smoother.

The role of birth and death are very central in Darwinian evolution theory. Now the system is more important than any individual; life is in the system, and in the population of individuals. As long as the system survives, there is no actual death. Another point is that because the genes only offer the pool of alternatives, the properties of an organism being mainly determined by the environmental conditions, one specific gene combination does not have such a crucial role.

Comparing to the Darwinian theory, again there is the match criterion that plays a central role. However, now it is not about the search for the absolutely best fit — the population-level system searches for a *set of good fits* to implement a good mixture model, to better capture all aspects of the nonlinear environment. Indeed, the essence of modeling of the environment is not to find the actual winner, but to *find the definition of what fitness is* and map the whole "fitness landscape". And the primary reason for diversity is not to be prepared for the unknown future — the reason is simply to exploit the prevailing environment as efficiently as possible, now and here, with no future prospects.

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[1] What is more, one needs to remember that the environment is not a predetermined entity, but it consists of other ever-adapting subsystems, and a stubborn individual can change its environment to make a new personal niche exist

There are many intuitions that are available here. For example, it has been wondered why the ecosystems seem to be fragile — after periods of steady developments, there come ecocatastrophes (Rohde and Muller, 2005); many developments in nature seem to be stepwise, “saltationistic”. Exploiting the control engineering understanding (Åström and Wittenmark, 1989), such turmoils can now easily be explained: As the cybernetic system is an adaptive control system, the problems that plague the technical controls also become manifested in natural systems. When the control gradually becomes *too good,* the natural dynamics cannot any more be identified — meaning that the control deteriorates, and the system can collapse if unanticipated disturbances enter the system.

There are also more fundamental consequences. For example, it seems that the evolutionary systems where structures emerge proceed against the arrow of entropy, meaning that they are thermodynamically somehow eccentric. However, in the cybernetic perspective, this all becomes fully consistent: From the entropy point of view, the sophisticated control structures are beneficial as they make it possible to better reach the “heat death”, or loss of information (variation) in the environment. Rather than fighting against entropy, the cybernetic systems — when their boundaries are appropriately determined — maximally increase entropy in their environments.

Still more philosophical discussions are motivated here — it seems that the cybernetic approaches can contribute to the very basics of model thinking. Traditionally, it is accepted that modeling can only capture a shadow of the essence of the real system. But as it is nature, too, that tries to construct models of environments, what is the difference? If a human analyses an ecosystem — applying appropriate modeling principles — does the resulting model differ in some fundamental way from the model that is constructed by nature? It may be that *interobjectivity* is possible: A model can reflect the essence of the reality itself.

5. CONCLUSION

The traditional Darwinian thinking suffers from intellectual discrepancies: For example, whereas the evolution mechanisms and fitnesses are defined on the level of individuals, the results are visible and meaningful only on the emergent level of the whole population. The lower and higher levels are traditionally incompatible, but in neocybernetics both levels are combined in the same model framework, the individuals being submodels that together constitute the systemic model of the species — and the individual species further being submodels that together constitute the systemic model of the ecosystem. Thus, one can proceed from the analysis of individuals to analysis of populations, and from the analysis of species to the analysis of ecosystems; and if one can extend from the analysis of the existing taxonomies to the spectrum of possible ones, from characterizing details to seeing larger patterns, perhaps biology (and ecology) someday become real sciences.

The above discussions extend the study of what life is from *actual* to *potential.* Indeed, if one defines

> *life is a higher-order dynamic balance*
> *in an environment*

the life sciences (and also social sciences, etc.) become integrated in the body of natural sciences. Biological life just resides in the chemical environment, whereas “social life” resides in the memetic ideasphere. And the new view does not only apply to analysis: When speaking of synthesis, neocybernetics can offer fresh intuitions to, for example, research on artificial life (Emmeche, 1994) and genetic algorithms (Holland, 1992).

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