Emergent Behavior in Sensor/Actor Networks in the Neocybernetic Framework of Elastic Systems

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Abstract

If one wants to describe emergent behavior in real-life systems, the framework of *neocybernetics* offers good possibilities. Neocybernetics deals with the modeling and control of complex real-life systems and it can be shown that emergence appears in terms of self-stabilization and self-organization. In order to gain reasonable results, multivariate statistical tools are applied. A new approach in the fields of neocybernetics are *elastic systems*. These systems are defined by a strong mutual interconnection with their environment in the form of material and/or information flow from and into the system. Elastic systems are better described by dynamic than static balances; if external forces influence the system, these forces are compensated by finding another equilibrium state, but if the forces are taken away again, the original system state is restored. The new approach offers the opportunity, for example, to control systems with distributed sensor/actor networks. It can be stated that emergent behavior pops up, even if there are no explicit communication structures among the sensor/actor nodes. This paper introduces the ideas of elastic systems in terms of simulations of the distributed control of an elastic steel plate.

1 Introduction

In the field of Artificial Intelligence, the need for decentralized approaches is increasing — it has even been said that the letters AI today mean Ambient Intelligence, or Agent Intelligence. Even the basic books in AI have adopted such agent perspectives (Russell and Norvig, 2002). However, despite the immediate need for conceptual tools for managing decentralized architectures, there exists no general theory: The applications are pragmatic software products that cannot be analyzed in mathematically efficient ways. The problem is that of differing semantics in different fields — the ontologies and the goals are domain-specific.

What if one could define some universal measure for semantics that would be applicable in any field? Indeed, this is pursued in *neocybernetics*, where the key concept is *information* as interpreted in a very pragmatic way: Information is manifested in (co)variation among data items (Hyötyniemi, 2006b). The goals of the actors are assumed to be always equal — they want to survive, selfishly trying to capture as much of the available information as possible. It turns out that *self-regulation* emerges because there is feedback through the environment: Resources being exploited are exhausted. What is more, there is *self-organization* in the system in terms of multivariate statistical constructs (principal subspace analysis, PSA), principal components emerging from the adaptation processes, making it possible to analyze the system also on the holistic level (Hyötyniemi, 2006b).

It is a nice coincidence that the goals of the individual actors — exploitation of information in the form of variation — happens to equal the goals of regulating controllers. This makes it possible to implement very simple agent-based controllers: There is no need for explicit communication among agents.

This approach of emphasizing the connection to one's environment resembles the Brooksian subsumption thinking (Brooks, 1991): The world itself is the best model of the world, and observation data is directly employed for appropriately adaptating the model structures. Even though such thinking cannot be applied in too complicated tasks, in special cases, like in control tasks where the simplified view of semantics is appropriate, it can be beneficial. There is

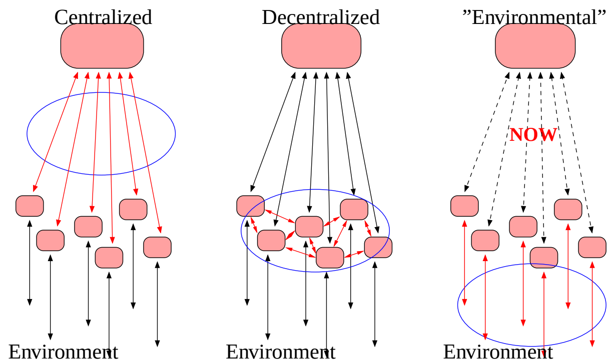


Figure 1: Communication and coordination among low level nodes.

no explicit communication among agents needed — whereas in traditional agent systems the operation is either centrally coordinated or negotiated among the agents, now it is the agents that only look after themselves (Figure 1).

A new interpretation of neocybernetics describes complex systems as *elastic systems* (Hyötyniemi, 2006a). These systems are in strong interconnection with their environment and characterized by material flow from and into the system; the system can not be regarded isolated, as it is embedded in its environment: changes in the environment affect the system and changes in the system itself affect the considered environment respectively. In the framework of elastic systems, decentralized control of elastic deformable systems — following the idea of dynamic equilibria — can be realized with distributed sensor/actor networks. As an example a steel plate, exposed to different external forces, is studied in a simulation environment (Sailer, 2006). It turns out that the adaptation process stiffens the considered system. Moreover, the completely adapted system can be described in terms of *constant elasticity*; the structure is adapting towards the maximum experienced stiffness.

2 Towards intelligent behavior in sensor/actor networks

There exist many industrial processes where systems can be described in terms of partial differential equations with distributed parameters. Generally, the complete information in these systems is not measurable, as the process state is infinite-dimensional. However, a reasonable setup to capture the necessary information is that of distributed sensor/actor networks: the infinite-dimensional system state is mapped on the finite amount of applied sensor/actor nodes, maintaining the distributed characteristics of the system.

Today's challenge is the orchestration of these networks, so that emergent behavior can evolve in these systems, or, in other words, so that the network behaves in an *intelligent* way. Conventional approaches concentrate on the search of the global structure of the sensor/actor network — but if one knows this picture, the coordination can also be performed in a centralized manner. What is more, the centralized scheme has yet another disadvantage: centralized implementation often represents the originally distributed structure of the systems very poorly.

The common framework for distributed systems is the *agent* perspective Lesser et al. (2003) but these studies have so far no consistent mathematical framework. Theories are often qualitative and do not offer concrete design methods.

Neocybernetics offers a consistent mathematical framework that could be applied in truly distributed sensor/actor networks. In these networks, the single sensor/actor nodes are capable of some limited computation and communication structures could be implemented for example with simple protocols. In these networks, the human can be detached from the process, the network is acting in a completely autonomous manner, assuming that the simple view of information can be accepted (Hyötyniemi, 2006b). One application example is the research of emergent coordination of distributed sensor networks (Hyötyniemi, 2004).

In the case of elastic systems, the balancing of the system is implemented implicitly, through feedback from the environment. In such environments, emergence can be reached with no explicit communication among the sensor/actor nodes whatsoever; every node is working on its own, but still, intelligent behavior can be found as shown in 5. In what follows the basic components of the networks, the agents, are called nodes. The nodes are identical and they can measure their environment (sensors) and influence the environment respectively (actors).

3 Elastic systems

This chapter introduces the ideas of elastic systems in general and its mathematical framework is presented.

3.1 Feedback through environment

In traditional control, the information of the participating nodes is collected and evaluated by central units in order to coordinate the system in the desired direction. Distributed modeling approaches concentrate on explicit communication structures among distributed actors. It turns out that new thoughts on elastic systems lead to emergent behavior also in truly distributed systems. The essential difference compared to the other two approaches is the existence of an implicit feedback structure directly through the environment itself. Figure 1 presents the new framework of elastic systems compared to the traditional approaches. The steel plate gives an excellent example for the understanding of this implicit feedback. If there are forces acting on the plate, these forces induce counter forces, according to the measured deformations of the applied sensor/actor nodes. These counteracting forces are directly measurable by other sensor/actor nodes, as they change the steel plate deformation, although the nodes do not have any active communication structure.

3.2 Mathematical considerations

Elastic systems are systems in dynamic equilibrium; if some *forces* are applied on the system, these forces cause *deformations* in the system, but if the forces vanish, the original state of the system is restored again. In the context of elastic systems the physical interpretation of forces and deformations can be different but the overall behavior of the system remains the same: For example, in chemistry this phenomenon is called *Le Chatelier Principle*. There, the dynamic equilibrium of chemical reactions drifts in another balanced state in order to counteract external changes. This abstraction level of elasticity offers a wide scope of applications (Hyötyniemi, 2006a).

The dynamic equilibrium of an elastic system — or the visible, emergent system model — is often expressed as

$$A\bar{x} = Bu. \quad (1)$$

Here, $\bar{x} \in \mathcal{R}^n$ describes the balanced system states x ($\lim_{t\to\infty} x = \bar{x}$), dependent on the measurable system input $u \in \mathcal{R}^m$, with $n \leq m$. In dynamic equilibrium, the system vector $\bar{x}$ can be solved explicitly, assuming that A^{-1} exists and there holds

$$\bar{x} = A^{-1}Bu = \phi^T u. \quad (2)$$

As elastic systems are in strong interconnection with their environment, caused by a feedback $-\varphi x$ from the system back into the environment, there exists a balanced state $\bar{u}$ for the system environment u and there holds

$$\bar{u} = \underbrace{u}_{\text{actual environment}} - \underbrace{\varphi\bar{x}}_{\text{feedback}}. \quad (3)$$

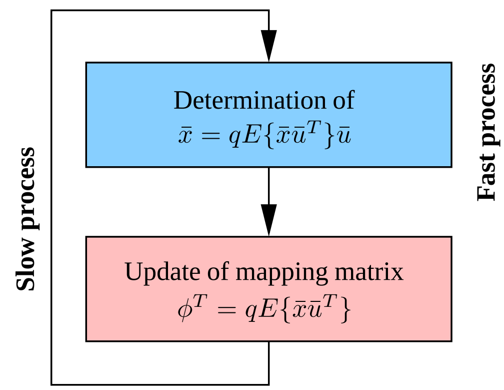


Figure 2: Flowchart of the adaptation process.

As the system sees only the balanced environment $\bar{u}$, (2) results in

$$\bar{x} = \phi^T\bar{u}. \quad (4)$$

The mapping matrix ϕ^T can be motivated by the *evolutionary fitness* (Hyötyniemi, 2006b) of complex real-life systems and then there follows:

$$\phi^T = qE\{\bar{x}\bar{u}^T\}. \quad (5)$$

Matrix $E\{\cdot\}$ denotes the covariance matrix. The constant factor q describes the strength of the interconnection between system and environment and can be interpreted as a *stiffness ratio*.

It is the mapping matrix ϕ^T that determines the emergent behavior. If one studies (4) and (5) closer, it can be seen that the solution for the mapping matrix has to be found iteratively as the balanced system states $\bar{x}$ and the balanced environmental states $\bar{u}$, determining the covariance matrix $E\{\bar{x}\bar{u}^T\}$ are not known beforehand. Therefore, the adaptation can be described as follows (see Fig. 2):

1. A fast adaptation finds the balanced system state (4), when external forces are applied on the system, causing deformations.

2. A slower process determines the mapping matrix ϕ^T. The system learns from different applied external forces and the overall balance is found, after the mapping matrix ϕ^T has adapated and does not change any longer — a *second order balance* is found.

For the validity of the adaptation process it is assumed that the change of the external forces is much slower than the determination of a balanced system state with (4). How the streamlining is realized can be read in (Sailer, 2006) and (Sailer and Hyötyniemi, 2006).

With the use of (5), the adapted system results finally in a balance, where the covariance matrix $E\{\bar{u}\bar{u}^T\}$ has the property

$$\frac{1}{q}I_n = \bar{\theta}^T E\{\bar{u}\bar{u}^T\}\bar{\theta}, \tag{6}$$

and there holds $\bar{\theta}^T\bar{\theta} = I_n$. It turns out that the columns in θ span the subspace determined by the n most significant principal components of $E\{\bar{u}\bar{u}^T\}$ (Hyötyniemi, 2006b). For more information on principal components, see (Basilevsky, 1994). Besides this equalization of variances, it can be seen that all eigenvalues $\bar{\lambda}_j, j = 1, ..., n$ of the closed loop equal $1/q$, meaning that the system becomes stiffer compensating the external applied forces. In this context one can speak of *constant elasticity* of the system.

In (Hyötyniemi, 2006b) it is shown that the latent system variables $\bar{x}$ can be chosen freely as $\bar{x}'$. This property makes it possible to apply *active control signals* as system variables no matter how the controls affect the environment. If there were complete information, all sensor/actors knowing all inputs, they still together implement principal subspace analysis. As this happens regardless of the mechanisms of actuation, it turns out that a cybernetic set of controllers *changes the environment* to match the theoretical model.

In this paper this sensor/actor scheme is simulated to set up the distributed control of an elastic deformable steel plate. Such a mechanical environment offers a nice test bench as the effects are delayless, and the local balances after force/counterforce application are found immediately (in principle — when the environment is simulated, there are additional issues, like balance problems). Here the information is not complete; it is assumed that each actor only is aware of its own local sensor. This means that the behaviors become strongly localized, but here, too, inter-agent organization takes place as there is blurring between the effects of individual actors along the steel plate.

4 Distributed control of an elastic deformable steel plate

A control scheme for a steel plate using a sensor/actor network, consisting of m sensor/actor nodes, was implemented. The measured steel plate deformations s define the environmental variables u, caused by some external applied forces F_{ext}. The induced actor forces F_{act} are the latent freely chosen system variables x' so that there holds:

$$\begin{cases} F_{act} &= x' \\ s &= u \end{cases} \tag{7}$$

If one assumes that there are no communication structures among the participating sensor/actor nodes, the mapping matrix ϕ^T is realized diagonal. In this case, the single actor forces $\bar{F}_{act,i}$ are only determined by their own measured sensor information $\bar{s}_i$.

Despite this simple learning, a global emergence can be observed in the simulations: with the introduced local adaptation and the fact that there are m sensor/actor nodes applied on the steel plate, there follows from (6)

$$\frac{1}{q}I_m = E\{\bar{s}\bar{s}^T\}, \tag{8}$$

with $E\{\bar{s}\bar{s}^T\}$ diagonal. With this relationship, the coupling coefficient q can be used in order to predict the emergent steel plate deformation after the system has fully adapted. The variances $E\{\bar{s}_i^2\}, i = 1, ..., m$ are directly determined by q. Therefore two different behaviors can be stated out in the adapted system:

- There is a loss in the variations $E\{\bar{s}_i^2\}, i = 1, ..., m$, meaning that the system is getting stiffer.
- The variances are all equalized by the factor $1/q$.

This observation is crucial, as the coupling coefficient q determines already *before* the start of the adaptation process, how the emergent shape of the (observed) steel plate looks like.

5 Simulation

This chapter shows in simulation examples, how emergent behavior evolves in case of the adaptation process of the steel plate, and interpretations are offered afterwards.

5.1 Results

The studied square-form steel plate has the dimensions $0.8 \times 0.8[m]$, and it is $0.01[m]$ thick. On the plate four sensor/actor nodes are placed as shown in Figure 3. The applied external forces are uniformly distributed between $-550[N]$ to $-600[N]$ for the second order adaptation. For the fast process these forces are constant (denoted as set l in the figures). In total 10000 different sets of external forces are used for the system adaptation. The studied steel plate is fixed on opposite sides. At these sides, the displacement of the steel plate is zero ($\Delta s = 0$).

Figure 4(a) shows the development for the measured displacements of the sensors during the ongoing adaptation process and Figure 4(b) the developing actor forces respectively. It can be seen that the system is getting stiffer with the ongoing adaptation process, as the actor forces are growing and the measured sensor displacements are getting smaller. The property of constant elasticity, mentioned earlier can be seen; the variances $E\{\bar{s}_i^2\}$ are equalized with the factor $1/q$. In the example, the coupling coefficient q has a value of $q = 4.5 \cdot 10^7 [1/m^2]$. According to (8), the variances $E\{\bar{s}_i^2\}$ are

$$E\{\bar{s}_i^2\} = 1/q = 2.22 \cdot 10^{-8} [m^2], \quad i = 1, ..., m. \tag{9}$$

As the variation level in the external forces is low, the expectation values of the measured displacements $E\{\bar{s}_i\}$ can be approximately determined directly from (9) as

$$E\{\bar{s}_i\} = 1/\sqrt{q} \approx \pm 1.49 \cdot 10^{-4} [m], \quad i = 1, ..., m. \tag{10}$$

Figure 4(a) shows that the expectation values $E\{\bar{s}_i\}$ are equalized on the level determined by (10); before the adaptation process takes place the sensor displacements are differing for the single nodes. Before convergence, there is exponential growth in the parameters and in the sensor forces; only after the effects in the system are noteworthy, there is feedback from the environment and the adaptation process stabilizes.

Figure 4(b) reveals different developments in the actor forces; those sensor/actor nodes where higher or more frequent deformations are measured are evolving stronger than nodes that are closer to the fixed boundaries or that are less deformed. Actor forces 3 and 4 are developing stronger than the forces 1 and 2 as they are closer to the applied external forces (see Figure 3). Force 1 is completely fading away, meaning that the sensor/actor node is not actively participating in the compensation after the system is fully adapted. In this case, sensor/actor node 1 can be described as *sub-cybernetic*; the global emergent goal of constant elasticity is reached, but the node does not play a particular role in the adapted system.

If the coupling coefficient q increases, all nodes are becoming active in the adapted sensor/actor network. Figures 5(a) and 5(b) show the results in the case of $q = 7.0 \cdot 10^7 [1/m^2]$. Here, once again, the final goal as determined by the coupling coefficient q is reached as $E\{\bar{s}_i\} = 1/\sqrt{q}$ holds, but all nodes are participating. In this case one can speak of a *fully cybernetic*

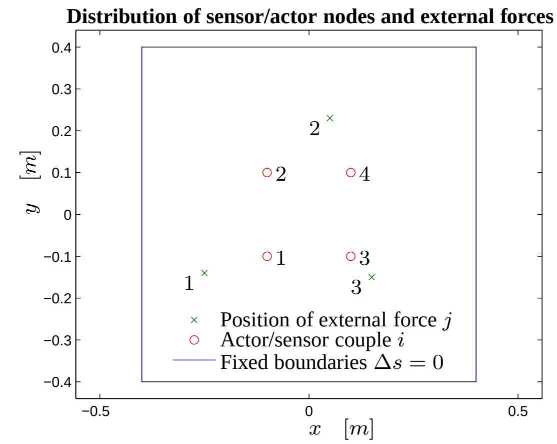


Figure 3: Steel plate setup.

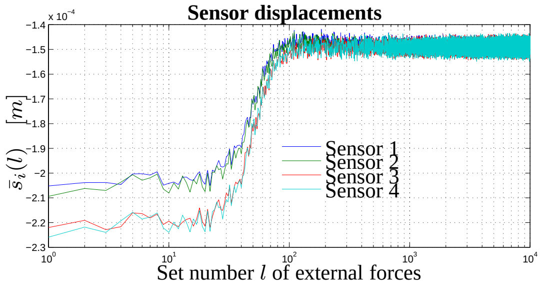
system. A deeper analysis on the coupling coefficient q and the influence on the emergent pattern in the sensor/actor networks can be read in Sailer (2006).

5.2 Interpretations

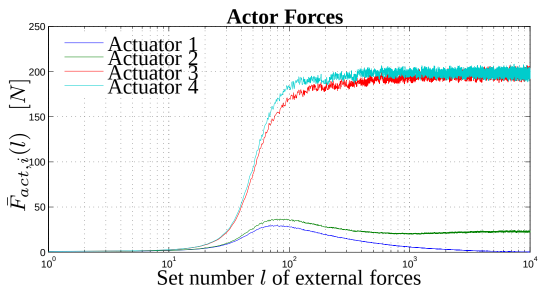
It has to be emphasized that despite the simple learning structure of the sensor/actor network emergent behavior can be observed in the elastic deformable steel plate. Although there are no communication structures among the sensor/actor nodes, the system finds a state of constant elasticity after the adaptation process. The sensor/actor nodes are communicating implicitly, as induced actor forces are measured as deformation changes by the other sensor/actor nodes.

If one compares the adaptation with conventional control tasks, the advantage of the proposed approach is obvious: there is no need of long lasting system identifications to achieve emergent behavior with the applied sensor/actor network. The nodes are adapting without the explicit knowledge of the global picture.

As one takes a closer look at the development of the actor forces during the ongoing adaptation process, one can observe that the behavior of the actors can be described as somehow *intelligent*. The global result of the adaptation is the stiffening of the steel plate on a constant level. As it can be seen in the first simulation example, nodes can vanish completely. These nodes are not necessary for the global emergence and therefore are dying. Their faith depends on how close they are to the *source of concern*. Sensor/actor nodes at more flexible positions, or at positions with more frequent or stronger occurring forces are developing stronger than nodes that are closer to boundaries or where external forces cause smaller deformations.

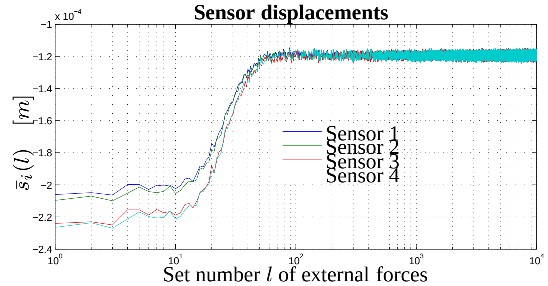


(a) Displacements.

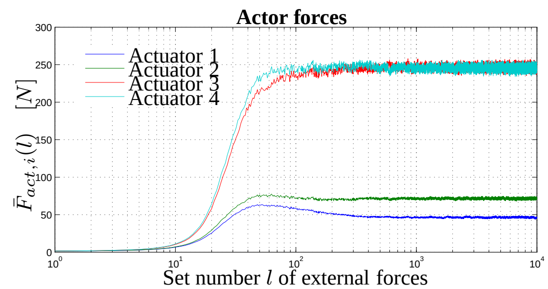


(b) Actor Forces.

Figure 4: Adaptation process of the steel plate, $q = 4.5 \cdot 10^7 [1/m^2]$.



(a) Displacements.



(b) Actor Forces.

Figure 5: Adaptation process of the steel plate, $q = 7.0 \cdot 10^7 [1/m^2]$.

It is easy to make hypotheses here. In biological systems such stiffening behavior can be observed as well: human cells are growing stronger or more cells are produced, if more frequent or stronger external signals are influencing specific cell areas. Examples are the human skin or muscle cells. In biology, these phenomena are called hypertrophy and hyperplasia. The motivation of the mapping matrix ϕ^T, as defined in (5), describing local evolutionary learning, seems to achieve reasonable results that can be interpreted in a biological context respectively.

Also in less concrete cybernetic systems, such stiffening is commonplace: the controls become stronger, and degrees of freedom vanish. It does not matter whether such "evolution" is implemented by nature, or by human, as in social systems.

When studying *supply* and *demand* in product markets, for example, the steel plate analogies are again applicable. In economy, the real world of customer needs (the "steel plate") is infinite-dimensional and poorly structured as seen from outside. When an actor/sensor couple is applied in some location there, however, or when a product with specific properties is introduced, the market deforms to balance the supply and demand. Products that are poorly located — if there is no demand (deformation) or if there are other better products nearby — soon fade away. As studied closer in (Hyötyniemi, 2006b), such analogies also make it possible to study the age-old philosophical questions in a new setting:

> "Is there any demand if there is nobody to supply?"

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