FROM NEURAL NETWORKS TO NEURAL STRATEGIES

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ABSTRACT

Artificial neural network have evolved from their biologically inspired roots to a well established means to solve a broad spectrum of engineering problems. The embedding into modern statistics has provided the necessary theoretical foundation for challenging engineering tasks, such as advanced real-time image and signal processing. These are exemplary demonstrations for the applicability of this approach to complex information processing. However, the large number of applications must not obscure the fact that there are some major unsolved problems concerning neural networks. There are still no satisfactorily constructive ways to determine the optimal structure (elements as well as organization) or the learning and evaluation dynamics. The ongoing research addresses these problems. In addition to pursuing this direction, one can ask, what other lessons we can learn from biology concerning complex information processing. Our goal in this paper is to sketch a possible way from neural networks to more comprehensive neural strategies.

1. INTRODUCTION

Artificial Neural Networks have found widespread acceptance for being robust systems for information processing in noisy environments. Intensive research from many different perspectives, such as statistics, theoretical physics and signal processing as well as numerous applications have taken some of their myth away [1, 2, 3, 4]. This is of advantage for the whole field of neural computation. Therefore, we believe the time is right to concentrate on the identification of the principles underlying neural information processing. From this perspective we hope to be able to propose some of the "neural strategies" as we termed it. In order to move on from neural networks to neural strategies we have to identify the *strategy* with which natural information processing systems operate in natural environments. These thoughts are by no means solely restricted to neural systems, however they apply to all kinds of natural information processes, such as evolution. A key question in identifying the neural strategies is phrased as the "problem of architecture" of information processing systems. We observe that biological systems are organized completely different than man made computing systems, however what are the principles underlying this structuring process? We believe that any proposal for the solution of this problems has to be strongly coupled to applications, which at our institute mainly belong to the problem classes of vision and autonomous behavior. We do not see this strong coupling mainly from an engineering perspective but also from a more fundamental point of view. The problem domain defines the structure of the solution for which we seek which design principles.

We commence with some recent applications of "classical" artificial neural networks, propose a way to more global neural strategies and try to show their applicability in the remainder of the paper.

2. RECENT APPLICATIONS OF NEURAL NETWORKS

Supervised artificial neural networks mainly represented by multi-layer perceptrons (MLP) and radial basis function networks (RBFN) [1] are an efficient means to solve information processing problems. Two exemplary applications from the problem domains dealt with at our institute shall serve to underline this statement. Besides these applications, the method of neural networks is subject to current research as well, for example see [5, 6].

2.1. Real-time video based car detection and tracking

There exists a long tradition of automotive related real time computer vision and signal processing problems at our institute. Within the framework of these projects, established as well as lesser known types of neural networks are employed for classification/object recognition and prediction tasks. A typical scenario here is to detect and track cars as well as other vehicles in images taken from German *autobahnen*. In different approaches neural networks in conjunction with a problem-adequate preprocessing are utilized to solve the essential subproblems [7, 8].

2.2. Nonlinear dynamics and times series analysis

In one of our other major research fields, nonlinear dynamics and times series analysis, neural networks are employed as well to approach the given tasks. In [9] it is shown, how to use the so called neural gas algorithm to improve the quality of a phase space reconstruction of a chaotic time series. Here, preprocessing for and with neural networks is employed to increase the robustness of the whole system.

3. NEURAL STRATEGIES AND PRINCIPLES

3.1. Principles

Neural networks follow a certain number of principles that can be formulated in a more general fashion and completed by a set of additional, biologically motivated principles. The following discussion is lead by (but is not limited to) the problems occurring in robotics due to the exemplary nature of the involved subtasks such as vision, navigation, representation and interaction with the environment.

In general the function of a system is decomposed into several sub-functions. The technological or algorithmic realization of these sub-functions can be interpreted as basic elements or modules. The structure of their coupling is determined by the solution of the given task. Therefore, the design of a system demands the solution of two problems: The identification of modules and the realization of a coupling strategy. Both problems cannot be solved independently, because the definition of modules determines the space of combinatorially possible solutions. We will call this the "problem of architecture". The basic elements and their couplings have to fulfill different task dependent constraints, for instance simple technical realizations or a large adaptation space where solutions are learnt.

There are several system architectures for different task domains, for example the structure of computer or control systems. It has been shown that those architectures do not cover all problems of modern system design. At the moment there is no systematic solution which can deal with the complexity, the nonlinearity and flexibility necessary for systems designed for natural environments. On the other hand, these tasks are successfully solved by biological systems. With this motivation, the summarized work following below tries to apply biological principles to the solution of well defined technical tasks. We have to face the problem to rely on incomplete knowledge of biological systems.

The principles we propose require definitions on different levels of abstraction. First, we propose general principles underlying biologically inspired information processing systems, and in the next section we will introduce definitions on the level of the specific problem domain of robotics and general visual processing tasks.

- Modules and especially their couplings are determined by the behavior of the system that has to be implemented. Coupling has to be realized on different levels since the pure combination of integrated behaviors (for example within the subsumption architecture [10]) leads to an insufficient number of entire behaviors.
- We aim at a constant structure of the process, while different functionality is achieved by variation of the data space.
- The processes are generally organized in a two-dimensional space and obey strong causality. This implies small changes in signal space cause small changes in the representation of the system. It corresponds to a trade-off between security and precision.
- The system behaves active in the sense that information processing determines the amount and character of the incoming data stream. An active camera system is a special case of this principle.
- If possible, invariance classes are build by compensation. The parameter against which the function should be invariant is controlled to zero. An example is the fovealization in order to reach position invariance.
- Learning is always related to a function, distributed among all levels of the system and operates on different time scales (hierarchy). Therefore, coding of knowledge depends on the structure of the system and has to be adapted to different subtasks.
- Representation of aspects of the environment (for example motion, depth, and so forth) is organized in relation to the behavior.
- Non explicitly solvable problems are formulated implicitly and solved by evolution and ontogeny oriented optimization approaches. This corresponds to applying biologically oriented methods to design biologically oriented information processing systems.

For all those aspects there exist several arguments from biology [11] which are partially validated and supported by experiments, see for example [12, 13, 14].

3.2. Definitions

Besides theses conceptual conditions, our system needs the following definitions. Some of them can be seen as operational instructions for the implementation.

- Different aspects of the environment are extracted by a vision system. The resulting redundancy increases the reliability of the functions and allows specializations.
- Processes are organized to be time dependent and two-dimensional in space. We mainly use two types of equations given in different forms by

$$
\begin{aligned}
u(\mathbf{x},t) &= \Phi(h(\mathbf{x},t) * s(\mathbf{x},t)) && (1)\\
\tau\dot{u}(\mathbf{x},t) &= -u(\mathbf{x},t) + h(\mathbf{x}) * \Phi(u(\mathbf{x},t)) && \\
&\quad -I + s(\mathbf{x},t) \quad \text{with} && (2)\\
s(\mathbf{x},t) &= \sum_i w_i(\mathbf{x},t)\, u_i(\mathbf{x},t) \quad . && (3)
\end{aligned}
$$

  Equation 1 characterizes the nonlinear function Φ of a convolution in space and time between a filter kernel h and an input s. Equation 2 describes the dynamics of the neural field u as proposed by Amari [15]. It can be interpreted as a combination of convolution and nonlinear feedback. Equation 3 describes the input of multiple external signals $u_i(\mathbf{x},t)$ into a single layer of neurons.
- Propagation of data between different subsystems can incorporate a coordinate transformation, for instance a mapping $\mathbb{R}^2 \mapsto \mathbb{R}^2$. The generation of a fovea is a special case.
- Discrete combinations of various two-dimensional representations in one layer constitute a method to gain functional specificity at the expense of spatial resolution with a task-dependent degree of parallelism.

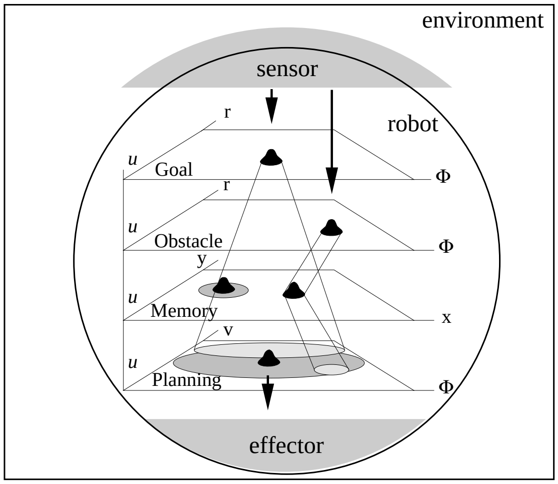

Figure 1: The dynamical neural field architecture for target acquisition and obstacle avoidance of a mobile platform. The two top layers representing sensed target and obstacle positions are treated as parameters here. The third layer represents memorized obstacle information. Planning and control occurs through a dynamics of heading direction at the bottom layer.

- Regularization enables the use of continuity assumptions in reducing information.

These definitions permit the description of the problems in a continuous space and imply a kind of "averaged anatomy" in biological terms.

4. APPLICATIONS OF NEURAL STRATEGIES

Several different applications have been implemented drawing from the previously mentioned principles. Many of them are integral parts of the NAMOS project [16] and its successor, the NEUROS project.

4.1. Exploration, Representation and Navigation

Neural fields have successfully been applied to the problem of representation and navigation in robotics. Information concerning variables such as position of the robot and obstacles, heading direction, speed and the like is encoded in the location of activations within the neural field. The temporal evolution of these activations governs the behavior of the corresponding variable. This formulation permits the natural introduction of concepts such as hysteresis, multistability, bifurcation and other concepts from nonlinear dynamics. Single neural fields can be used for subtasks such as to represent a map of the robot's environment, where the activation peaks correspond to the location of obstacles, or to control the heading direction based on maps of the obstacles, the target position and optical recalibration information. The overall behavior of the system is determined by the inter- and intra-field interactions of the activations [16, 12]. See figure 1.

4.2. Sensor fusion and collision avoidance

Once a target position is determined by some behavior, it is the task of the collision avoidance behavior to reach this position without colliding with obstacles. The collision avoidance is *time-to-contact* [17] based. The sensory systems provide multiple (possibly contradictory) information concerning this variable. These informations are integrated by representing them as forces in a neural field, each voting for a specific value of the behavioral variable. Using the implicit properties of the neural field equations, these forces are integrated and a single value is provide for the navigation system[18].

4.3. Vehicle Guidance

The above mentioned principles have also been successfully applied to an automotive related problem. The tasks comprises lateral and longitudinal intelligent vehicle guidance on *autobahnen*. The approach is based on distance and *time-to-contact* measurements of objects in the vicinity of the controlled car. The applied methodology resembles the dynamic field architecture where the information is again encoded in the location of activations within dynamic fields. The system is designed to make reliable decisions depending on the detected objects and the nominal velocity in the presence of disturbed sensory information. The control process results in typical driving behaviors like lane keeping, overtaking, and collision avoidance [19].

4.4. Structuring Neuro-Fuzzy Systems

The process of coding and optimizing the structure of a special class of neural networks, radial basis function networks, can be solved in connection with fuzzy inference systems. Takagi-Sugeno type fuzzy systems with Gaussian membership functions are functionally equivalent to RBFNs and there exists a unique mapping from the fuzzy system to the network. Evolution strategies for the optimization of parameters and genetic algorithms for the discrete optimization problem are used to obtain the best representation of the data set in the fuzzy system. In this process the rule base and the membership functions are adapted in parallel. After the inference system has been translated into the neural network, general learning techniques can be applied for further "fine tuning". The optimized networks have been used successfully for time series prediction and controlling tasks in the car industry [20].

4.5. Coding of neural networks for evolutionary optimization

The successful application of evolutionary techniques in structure optimization problems strongly depends on the right choice of the coding. The way in which the information about the network is stored determines the effect of the evolutionary operators, mutation and recombination, the scaling of the optimization process for large networks, and the structure of the network itself. We use a recursive encoding method for feedforward and special recurrent networks based upon the work of Kitano [21] for the coding of the neural networks. Genetic algorithms are then used to optimize the network structure and the weight initialization. After the optimization part, a learning algorithm is applied which specializes the network structure on the specific problem determined by the data set. The coding method itself is parameterized and optimized on a different time scale than the network in the same process. Applications are the prediction and especially the modeling of time series. The data stem from computer generated models and from measurements from industrial processes.

5. SUMMARY AND CONCLUSION

In this paper, we have tried to show that the principles underlying artificial neural networks belong to a broader class of biologically motivated design principles for complex information processing systems. The reason for dealing with this kind of issues is the superiority of biological over technical systems in natural environments. The possibility to adapt to a broad class of problems without the risk of instabilities, is one of the most important properties, which no technical systems has achieved yet. Drawing from the formulated principles, several applications from robotics, control and time series analysis have been presented to demonstrate the technical feasibility of the concepts.

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