INTRODUCTORY REMARKS TO SYMPOSIUM:

COMPUTATIONAL NEUROETHOLOGY AND ARTIFICIAL LIFE

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In behaving systems, the relation between structure and function is particularly intricate. The classical way to investigate this relation starts with behavioral competences and seeks to identify the anatomy and physiology of the underlying biological "hardware". Many parts of the biological machinery have been analysed in great detail and (neural network) models, mostly describing the dynamics of some state variable (activity, weights, etc.), have been developed (for an overview, see Arbib 1995). Some of these models have been very successful in describing and predicting neurophysiological results. Unfortunately, the functional interpretation of these results turns out to be far from obvious in many cases: What does the firing of a neuron mean with respect to the animal's behavior?

In recent years, therefore, there is growing interest in the reverse question, i.e., what functions can a given machinery generate (see Langton 1995, Steels 1995). When self-organizing systems are considered, this leads to the question of "emergent behavior", i.e., behavioral competences that were not anticipated when looking at the elements of the system. This approach to neurobiology can be called "synthetic". It has gained new interest by two recent developments:

1. Complex behavior exhibited by very simple systems has been studied in a number of instructive examples. Most notably, Braitenberg's (1984) influential book on "Vehicles" has focused the interest of many researchers on simple automata that seem to behave meaningfully. Besides actual robot implementations of behaving systems, computer simulated agents have become a powerful tool for the investigation of complex behavior in simple systems. The term animats is used for both real and simulated robots.

2. The adaptation of systems to given behavioral tasks has become possible by recent developments in the theory of optimization. Optimization procedures mimicking the process of mutation and natural selection in evolution (so-called "genetic" or "evolutionary" algorithms) have been developed that can bridge the gap between a desired behavior and a structure subserving this behavior.

The main point we want to illustrate in this symposium is that Artificial Life provides a theoretical framework for action and perception, i.e., for the interaction of systems with their environment. Information processing theories are largely theories of perception alone in which the usefulness of the recovered information for behavioral tasks is not addressed. The same holds for many neural network simulations (see Mallot et al., 1992). As a result, theories of both types often put great effort in recovering information, for which there is no real need in living animals. In contrast, the idea of Artificial Life (as opposed to mere Artificial Intelligence) leeds back to the notion of feedback loops and behavioral ecology (e.g., Krebs and Davies 1991) that link action and perception via the environment. Neural networks and information processing theories can still be used as building blocks within this framework. In addition, however, the question "What is information processing for?" can be answered with respect to some fitness measure of the system's performance in the environment.

By considering the interaction of systems with their environment, the notions of information and meaning are grounded in the performance of the system, i.e., in its fitness. This opens up a novel opportunity to study the evolution of information processing capabilities. If the performance of an entire system interacting with its environment in an action-perception-cycle is simulated, its fitness can be determined and subsequently be optimized with respect to the parameters or traits defining the system. The optimization strategies used are simulated evolution or genetic algorithms (for review see Forrest 1993). The parameters are stored as numbers or bit-strings simulating a genome from which the system can be constructed. Optimization is achieved in an iterative process starting from an initial population of individuals with a certain variance in their parameter sets (Fig. 1). After simulating their performance for a while and evaluating their fitness, the fittest individuals are selected and reproduced while the others are removed

from the process. Reproduction includes "mutation", i.e., new random variation of the parameters and also recombination of the parameter sets from parent individuals. By considering populations of individuals, local optima of the fitness surface can be avoided. Genetic algorithms can also be applied to coevolution of various interacting types of systems ("species"), in which case a global fitness function does not exist.

Artificial Life is a relatively new field of research bringing together neurobiology, computer science, robotics, and evolution. We hope that this symposium helps to better understand the different approaches and thus contributes to this exciting new field.

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