Genetic Encoding of Neural Network Processing and Control

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The search for useful genetic representations of neural networks has led to the successive development of direct, parametric and grammatical encoding approaches. (Yao, 1993; Happel and Murre, 1994; Gruau, 1995) Each of these approaches has, in turn, explored the inclusion of increasingly detailed specifications of neural network properties into the genetic representation. Incorporating increased knowledge into the encoding permits the representation of more complex and varied neural network models, permits the evolutionary search to manipulate more aspects of the network model, and reduces the assumptions required in interpreting the genotype to form a functional phenotype. The latter is important since any knowledge included in the interpreter is fixed for the entire space of genotypes and is thus unavailable for genetic manipulation.

Existing research has succeeded in representing only a small subset of the properties of typical neural network models. The focus has been primarily upon representing network connectivity, network weights, and simple learning parameters. The evolutionary search spaces thus contain networks with homogenous neurons, identical learning mechanisms (varying only by mechanism-specific parameters), and identical signal processing behaviors.

Our research (Hussain and Browse, 1998; Browse, Hussain and Smillie, 1999) extends the complexity of the genetic representation and reduces the complexity of the neural interpreter. We use a grammatical encoding approach, but adopt a model of neural processing that permits grammars to specify heterogeneous networks.

Our evolutionary system uses an attribute grammar (Knuth, 1968) to specify a class of neural networks. Each parse tree generated from the grammar depicts an individual neural network. The values of the attributes that are computed within the parse tree encode the connections among nodes of the network along with the characteristics of the operation of the nodes. Our current grammar collects this information in the attributes of the root symbol of the tree to form a concise neural network specification. The system's neural interpreter is able to accept this specification and carry out the functions of the network.

In our system, a neuron is considered a processing element which may receive signals of multiple types and may transmit signals of multiple types (e.g., activation and feedback). It may include arbitrary internal memory and internal functions that process the incoming signals, modify internal memory and produce output signals. This is in contrast to the typical neuron model in which the only signal is the activation signal. Finally, all functional behaviors of a neural network are considered to occur as local operations of its constituent nodes.

Through the use of multiple signal types, it becomes possible to explicitly include nodes and connections into the network that control the processing behavior of other nodes. As a result, the signal processing properties of the network may be genetically represented. For example, a grammar may include nodes which transmit control signals that other processing nodes may use to determine when to initiate or inhibit actions such as transmitting activation, transmitting feedback, or adapting weights. The particular set of control nodes specified in a network will determine the sequence of feedforward, feedback and learning operations. These control nodes carry out a different operation than the processing nodes, but those differences are only variations of the basic neuron model and thus do not require special treatment by the neural interpreter.

Our method of genetically representing neural networks has several useful characteristics. Firstly, depending upon the productions of the grammar, networks with highly structured or highly arbitrary connectivity may be created. Secondly, because a grammar may include different kinds of control nodes, it may produce neural networks with different processing and learning behaviors. Thirdly, the interpreter used to generate a functioning network from the parse trees of such grammars requires no knowledge of the architectural details of the model. During each cycle of the network, it simply executes the given processing function of each neuron and propagates the generated signals. Finally, changes to the underlying neural network model require changes solely to the grammar productions and terminal symbol characteristics. Changes to the neural interpreter are never required.

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