Proc. Int. Conf. on Artificial Neural Networks (ICANN), Helsinki, vol. 1, pp. 747-752, North-Holland 1991

GNOM - A MODULAR NETWORK ARCHITECTURE FOR ADAPTIVE PARALLEL/SEQUENTIAL PATTERN RECOGNITON

H.-M. Gross, E. Koerner, T. Pomierski

Department of Neuroinformatics
Ilmenau Institute of Technology
O-6300 Ilmenau, PSF 327, Germany

We propose a multi-layered Neural Network architecture which enables a knowledge based segmentation of a complex parallel input into a sequence of smaller scale parallel input segments representing known parts of the input to the system. The functional architecture described in this paper ensures selfregulation of relaxation and learning in a way the system can learn from experience by taking the known aspects out of an unknown input one by one.

1. INTRODUCTION AND MODEL HYPOTHESIS

Formal homogeneous Neural Networks provide a powerful tool for completely in-parallel pattern matching and classification. But systems for recognition of complex input pattern face the problem that with unknown or incompletely known inputs an in-time formulation of a hypothesis on the input is taking the risk of ending up in partial matches. The more complex the input the more serious the consequences of combinatorical explosion of the decision problems. Therefore in any cases other than restricted simple input patterns an attentional control of both relaxation and learning is a prerequisite to prevent this combinatorical explosion in completely parallel pattern matching.
The only way out of this dilemma is to include serial operations into the recognition process which are typical for higher visual and logic processing [1].

To guarantee a rapid and smooth recognition process, the associative search for a hypothesis on the input has to be guided by the systems recall itself which represents knowledge on parts of the input. To do just that the system has to be able to concentrate first on the known parts of the input which make already some sense to it, hereby selectively reducing the dimension of the accepted parallel input and shifting its focus of attention in the course of making the hypothesis globally consistent. Based on these considerations the basic ideas of our <u>model hypothesis</u> can be formulated as follows [2, 3]:

1. Complex inputs which are not consistent interpretable completely in-parallel (because of competitive decision alternatives about parts of the input pattern) will be knowledge based segmented into a time sequence of i) known input segments of smaller dimension and ii) remaining unknown input parts which cannot be segmented any deeper.
2. The already aquired knowledge has to control both the

Proc. Int. Conf. on Artificial Neural Networks (ICANN), Helsinki, vol. 1, pp. 747-752, North-Holland 1991

subsequent course of input segmentation and the process of learning the selected segments to known or new category representations.
3. Without external modulation or control the sequence of decisions is ranked exclusively according to the complexity of the accepted segments (dimension of active channels) and to the quality of matching with internal category templates.

Under this aspects we developed the modular network architecture **GNOM** (General Neural Operational Module) based on a selfregulating control structure enabling parallel-sequential recognition and autonomous learning as mentioned above [4,5]. It is worth noting that despite the different starting point and implementation of our approach compared to Carpenter & Grossberg's ART-systems [6,7] the functional characteristics are in some respect similar.

2. FUNCTIONAL ARCHITECTURE OF THE MODEL

The hypothesized architecture of GNOM is motivated by the very general feature of highly reentrant processing in the layered and columnar organized neocortex, regarding both intra- and intercolumnar communication. The model is a general one in the sense that it is not dedicated to any specific sensory input quality or recognition task. Hence the existence of appropriate feature preprocessing modules is assumed that submit a certain characteristic activity distribution as an input to the module.
The main elements of GNOM are illustrated in **Figure 1.** Any GNOM consists of two mutually communicating multi-layered subsystems composed of heterogeneous elements. The lower subsystem is called Interface Subsystem (IS) the upper one Category Subsystem (CS). Both subsystems constituting a dynamic control hierarchy are strogly interrelated both by information and control streams.

Identification of a complex input requires the freedom to select only those parts out of the input which are needed at that time in the recognition process. Operating on the Interface Subsystem the classifying Category Subsystem can actively modulate and manipulate the input pattern giving it the freedom of formulating and testing hypothesis on parts of the parallel input. It controls the interface and performs a random access grouping at the interface level to restrict the complex input to that needed for a smooth and rapid identification process.

The two subsystems are interconnected both bottom-up and top-down by adaptive filters based on special learning concepts (see point 3). Of special relevance for the relaxation and learning in the system is an adaptive filter at the **BCb** in the Category Subsystem which stores the several input segment categories as reduced inhibition to maximize the euclidean distance between the category weight vectors.
The Interface Subsystem (IS) consists of a layer of relay neurons **IN** being controled by a multilayered network of inhibitory neurons **BC**. The strength of this BC-inhibition across all IS-channels is modulated by the feedback from the Category Subsystem (CS) operating on the Interface Subsystem.

After presenting an input (known or unknown) to the **IN** of Interface Subsystem several decisions on the input are developing

Proc. Int. Conf. on Artificial Neural Networks (ICANN), Helsinki, vol. 1, pp. 747-752, North-Holland 1991

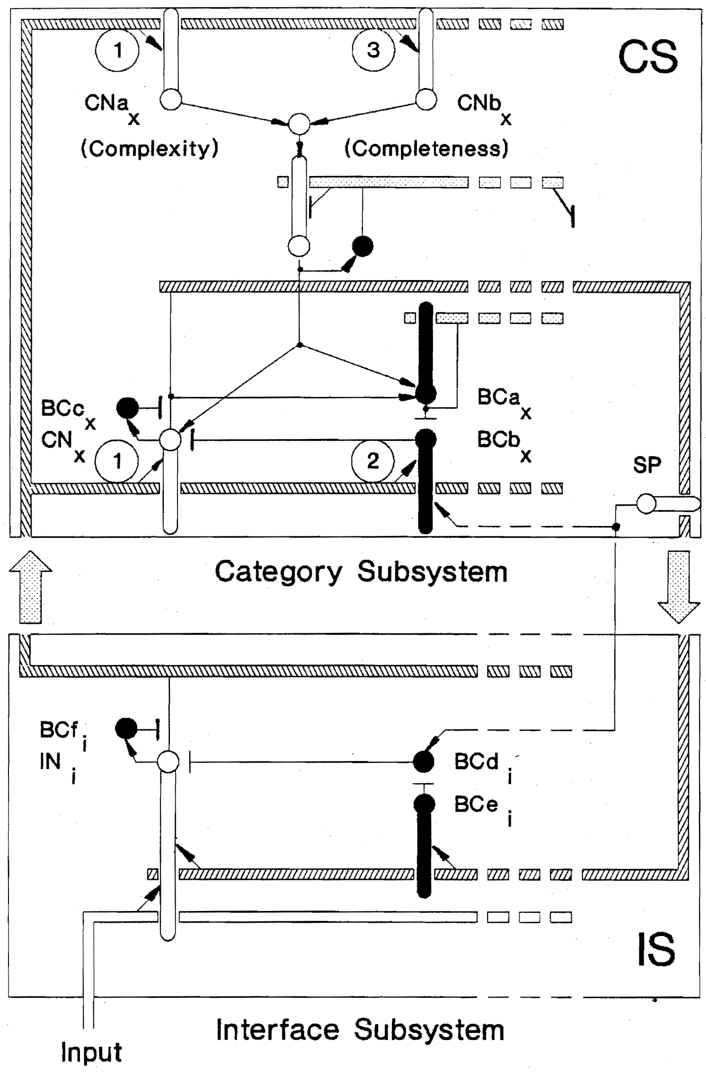

FIGURE 1

General architecture of a GNOM module for adaptive parallel-sequential pattern recognition. The nodes **CN** (category nodes),**CNa** (encoding complexity of input segments), **CNb** (encoding completeness of a learned segment) and **BCb** (encoding a kind of euclidean distance measure) constitute a **category representation group.** The complete Category Subsystem <u>CS</u> consists of many of these groups. For more explanations of the Interface Subsystem <u>IS</u> see text. The numbers in circles designate adaptive filters based on several learning concepts.

in **CN**-nodes at the Category Subsystem. The most active **CN**-decisions are fed back to <u>IS</u> like an expectation and disinhibit those **IN** nodes that are expected to be active if the decisions about the input taken in <u>CS</u> are correct according to the already aquired knowledge. This setting free of special <u>IS</u>-channels supposes an activity entrainment in <u>CS</u> strong enough to create an inhibitory level **SP** (selective pressure) at <u>IS</u> which can mask all other analog inputs. By this inhibitory masking the parallel input is drastically reduced to only a small dimension containing the best known aspects of the input the <u>CS</u> has to decide on.

Because of the closed loop of <u>IS</u>===><u>CS</u>===><u>IS</u> processing the modulated input is now fed back to <u>CS</u> and the processing cycle begins anew. The ensemble competition in the category subsystem suppresses alternative decisions with weaker competitive power so that in the next cycles only the strongest one survives which in the following slaves the module completely. The input is cleaned up towards this most active **CN**-decision, not fitting input segments and correspondending category decisions are completely suppressed by the inhibitory selective pressure (**SP**) in both subsystems. With entrainment of such a hypothesis on a subset of the input channels, the selected input segment is flashlike sent throughout both subsystems and subsequently switched off by special inhibiting neurons **BCc** and **BCf** (Figure 1). Switching off

Proc. Int. Conf. on Artificial Neural Networks (ICANN), Helsinki, vol. 1, pp. 747-752, North-Holland 1991

the entrained pattern is implemented by inhibiting the input channels at the Interface Subsystem that contribute to just this segment - hence the next decomposition is to be done without this already recognized part of the input. So the next-grade complex known input configuration will start this process anew and a new decision on the remaining part of the input can develop in CS. The so generated sequence of decisions is ranked according to its respective input segment dimension (complexity-coded in **CNa**) since the number of elements supporting a segment determines the related power in cooperation and competition for entrainment with alternative solutions.

In contrast to ART architectures generating iterated cycles searching for the best full parallel match between momentary input and selected best category pattern our sytem decomposes the momentary parallel input into a sequence of smaller dimensional segments representing known parts on the input. A match completely in parallel can develop only when the input pattern is entirely known and undistorted. The explained segmentation process represents a knowledge based internal input scanning.

In case of fitting to stored sequential knowledge in an associated system for dynamical pattern processing and memorizing [8] the sequence is rapidly reassembled and synchronized to a complete parallel representation matching all relevant channels at the input. This generated full-parallel input activation can finally be learned to a new complex category node **CN**.

3. LEARNING IN GNOM

The learning concept requires special internal control mechanisms to separate similar but discriminable input categories exactly. Therefore the Category Subsystem was designed to select internally the correct learning category by means of adaptive filter operations at the **BCb** layer in CS. In this concept that **BCb**-node whose activation by IS output is the lowest because of learning as reduced inhibition is selected automatically for learning the known or unknown part of the decomposed parallel input. The developed learning algorithm called bidirectional learning realizes a kind of euclidean distance maximizing.

From functional point of view the subnetwork of **BCb**-nodes constitutes an adaptive euclidean distance filter. The inhibitory energy of the **BCb**-neurons representing the sum of the weighted pathways is a dimensionless measure of that pattern match or distance. Because of nonlinearly maximizing the inhibitory energy in mismatching, only the category group (CN_X-CNa_X-CNb_X-BCb_X) the BCb_X of which has the lowest inhibitory energy can perform the segment learning selectively. All other category groups are inhibited completely so that the weight vectors of these groups remain unchanged.

For a detailed investigation of the bidirectional learning algorithm, its dynamics and separation properties see [9]. Another prerequisite to correct learning was the implementation of a special learning algorithm for the neurons **CN** and **CNa** which offers an equal chance even for patterns with different numbers of elements forming this pattern [3].

Since the real-time learning process in GNOM has to be unsupervised there exists no external teacher which defines what pattern at the Interface Subsystem is a known input segment or an

Proc. Int. Conf. on Artificial Neural Networks (ICANN), Helsinki, vol. 1, pp. 747-752, North-Holland 1991

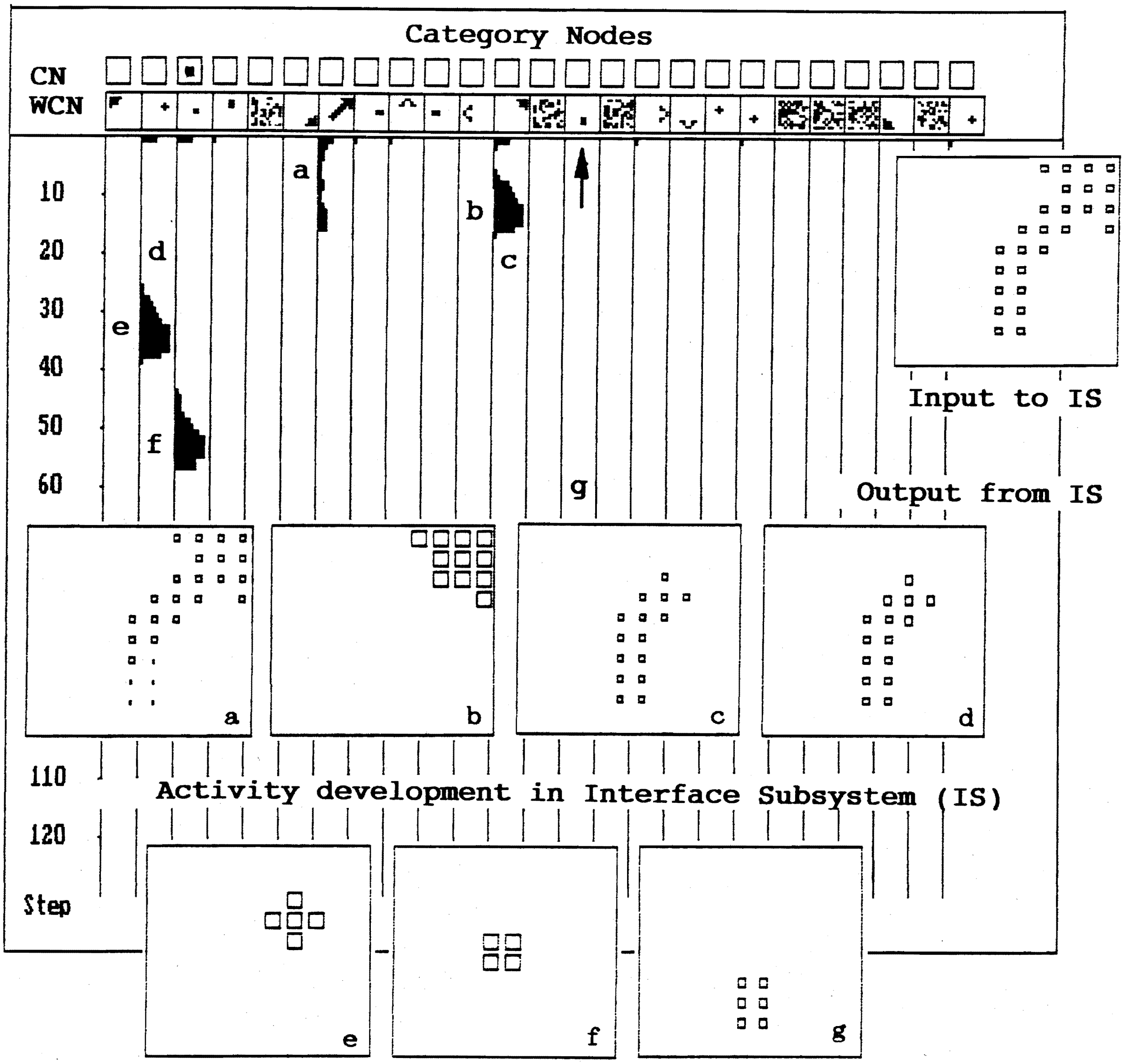

FIGURE 2
Computer simulation of knowledge controled input segmentation in case of fully-parallel not consistent recognizable input (unknown). Activity pattern a)-g) generated at Interface Subsystem IS show the segmentation sequence of formulating and testing hypothesis on the parallel input.

unknown new input part and what is noise. The only way out of this dilemma is to define, that all input configurations of certain minimal complexity (parts of input or the whole input) which can be stabilized in the Interface Subsystem for a definite time are appropriate candidates for learning. This temporal limited stabilization is the result of an complex dynamical interaction process between input activation, inhibitory masking by selective pressure, disinhibitory recalled expectation from Category Subsystem and switching off already recognized segments. Therefore an unknown input segment is defined as that part of the original input pattern that remaines in the Interface Subsystem as result of the temporal input decomposition and inhibitory masking of the recognized segments.

Proc. Int. Conf. on Artificial Neural Networks (ICANN), Helsinki, vol. 1, pp. 747-752, North-Holland 1991

4. SIMULATION RESULTS

Figure 2 demonstrates the recall in a system with already aquired knowledge about input segments. The aspect of the input with the highest complexity gets the lead in organizing the search for inputs fitting to it and starts the process of sequential recall (activity pattern a) b)). The channel-specific mechanism for inhibition after stabilizing a decision takes this decision for a certain time out of discussion (c). In a time sharing manner other CS decisions can evolve (d-f), thus creating a reverberating sequence of limited numbers of such decisions. Hence, the sequence is ranked according to the complexity (dimension of active channels) of selected input segments. Pattern (g) is an unknown remaining part of the input which cannot be segmented any deeper. Therefore it will be learned at CS as a new category.

A rapid synchronization back to a completely parallel representaion is only possible, if the completely complex input is already learned at CS as a parallel representation. In case of not yet having this knowledge, this stable reverberating sequence represents the state of knowledge of the system on this scene.

5. CONCLUSIONS

The model described is a minimum configuration for enabling a processing-state dependent attentional control which is a flexible self-regulating scheme with the potential ability to start-up, direct and sharpen the associative search in the distributed memory. The next step in application of our parallel-sequential recognition module GNOM will be the implementation of a large-scale multi-modular system for selective visual attention, whereby effects of intermodular communication between many Category Subsystems and of fast dynamical synaptic modulation for temporal synchronization of local decisions [10] will be objects of research.

References

[1] **Koerner, E** :Neurocomputing-What's on, what's real?; in studia biophysica, vol 132(1989) 1-2, p.127-136

[2] **Koerner,E.;Gross, H.M.; Tsuda,I.**: Holonic Processing in a Model System of Cortical Processors, in "Biological Complexity and Information" p. 86-116, World Scientific Publishing 1990

[3] **Gross,H.M.**: Simulation of an Array of Cortical Processors for Knowledge Controled Information Processing; PhD; Ilmenau Institute of Technology, 1989 (in german)

[4] **Gross,H.M. & Koerner,E.**: A Multi-Layered Mutually Communicating Neural Network Module for Adaptive Pattern Classification; in Proceedings of "NeuroNet 90", Prague Sept. 1990

[5] **Pomierski, T.**: Modular Pattern Classifier with Parallel-Sequential Processing Modes; Masters Thesis, Ilmenau 1990 (in german)

[6] **Carpenter,G.A. & Grossberg,S.**: The ART of Adaptive Pattern Recognition by a Self-Organizing Neural Network; IEEE Comp.(1988)3, 77-88

[7] **Carpenter,G.A.**: Neural Network Models for Pattern Recognition and Associative Memory; Neural Networks, Vol. 2 (1989) pp. 243-257

[8] **Boehme, H. & Koerner, E.**: this volume

[9] **Gross, H.M.** : in preparation

[10] **v.d. Malsburg, Ch. & Schneider, W.**: A Neural Cocktail-party Processor; Biol. Cybern 54 (1986) p. 29