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A MULTI-LAYERED MUTUALLY COMMUNICATING NEURAL NETWORK MODULE FOR ADAPTIVE PATTERN CLASSIFICATION

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S u m m a r y

We propose a multi-layered model and its functional interpretation on a possible layer III organization of a neocortical column, which enables a special type of distributed memory with a highly competetive and very definite object representation that is required for a rapid semantically based guessing (classification) as the start of an cortical interpretation process (see Koerner 87).

Keywords: Neocortex, Minicolumn, ART, competetive learning

The hypothesized architecture of the module 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 main elements of the R1-called module (repertoire 1, see Edelman 1978, Koerner 1987, Gross 1989) are illustrated in Figure 1.

The general architecture of the R1-modul is based on well known adaptive pattern recognition networks, often called competitive learning models (Grossberg 1976). Because the ART-models of Carpenter & Grossberg (1988) grew out of an analysis of this type of neural networks there are some functional similarities between the ART-models and our R1-modul. However, not the learning dynamics and the internal conditions for the learning process are the main points of our work but the development of a functional architecture of a biologically orientated fine structured multilayered neocortical subsystem which can very rapidly discriminate highly non-orthogonal input patterns with high efficiency.

Of special interest are some intramodular adaptive control mechanisms which are prerequisite for the desired rapid classification task.

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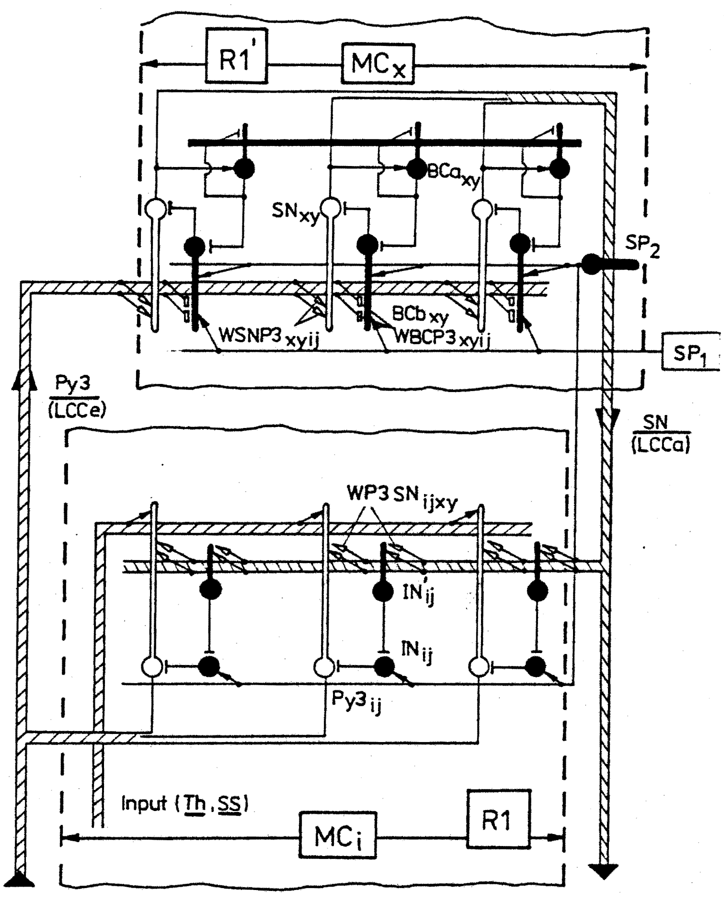

Figure 1:

Each **Py3**-output triggers to a different degree all trained representations at the **SN**-level because of its nonorthogonality. The ensemble competition in the upper subsystem suppresses alternative decisions with weaker competitive power and only the strongest one survives which in the following slaves the module completely. The input is cleaned up towards this SN-decision, not fitting input elements are suppressed by the inhibitory selective pressure (**SP**) both within **Py3** and **SN**.
If the associative dispersion of activity cannot be sharpened at the **SN**-level because of the power of each competetive solution being roughly the same, the selective pressure (**SP**) increases and overrules the feedback disinhibition. So it will depress or switch off Py3-elements beginning with the elements belonging to the weakest solution and stop only then, if at **SN**-level a more sharp solution can develop.
Contrary, if at **SN** no solution can develop, the selective pressure decreases adaptivly, making it more easy to evoke another internal, competetive representation.

The functional architecture and mechanism of the model are suggested by the known morphological data on the intracortical interactions esp. in the cortical layer III. For simplification only some of the known intracortical connections and mechanisms of single neuron function have been included.
The input layer Py3 serves as an interface for matching the input with recalled expectations (stored semantic knowledge) from the semantic layer SN. These two multilayered subsystems are interconnected both bottom-up and top-down by adaptive filters. Additionally, a third adaptive filter which stores several semantic concepts as reduced inhibition is implemented at the upper subsystem to the neurons BC (small bascet cells). Prerequisite to this multiple coding scheme is the implementation of a special learning algorithm which offers an

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equal chance even for patterns with different numbers of elements forming this pattern (Gross 1989).
If an input is presented to the Py3-neurons (general feature detectors) of the lower subsystem,those SN-decisions (category representations or pattern recall) are fed back to **Py3** like an expectation and disinhibit those **Py3**-nodes that are expected to be active if the decision about the input taken in **SN** is correct according to the already gained knowledge. So the memory traces are established via entrainment of reverberatory activity in disinhibitory (for weak SN-solutions with low activity levels) and nonlinear excitatory (for sharp solutions with high activity levels) feedback loops connecting the nodes in the **SN**-layer with the nodes in the input (**Py3**)-layer.
In this way the **Py3** input layer is modulated both by sensory input and semantic recall from **SN** and by an adaptively increasing or decreasing selective pressure (**SP**) in a way that the input is dynamically processed and reshuffeled according to the state of intramodular processing.
Switching off the not fitting input channels by SP-induced increase of the inhibitory level at the Py3-subsystem is a powerfull characteristics of the system to cope with a too high input complexity. Furthermore, with hiding the input channels activity behind the created inhibitory level, all possibly earlier established relations of these input elements are automatically erased. Those input elements can be freely arranged to any other order relation.
Regarding pattern recognition and classification this system has special abilities for the discrimination of highly non-orthogonal patterns with high accuracy.

R e f e r e n c e s

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