

THINKING AND LANGUAGE: EEG MATURATION AND MODEL OF CONTEXTUAL LANGUAGE LEARNING

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Abstract. A modeling of verbal modulation of information is an important but extremely complex task, still waiting to be fully accomplished in future hierarchical neural networks. However, it seems that basic brain mechanisms responsible for semantic/pragmatic/syntactic organization of natural language are known (Pribram, 1977). According to the oscillator model of Ellias and Grossberg (1975), the EEG rhythmicity is realistically predicted in such a way that an increase in the input causes an increase in the frequency of oscillations, and decrease in their amplitude, offering an unified explanation of EEG waves ranging from δ to γ) - which might basically be also the mechanism of information ascending upon the frontolimbic-amplification from the lower-frequency (δ , θ) unconscious form of primordial subliminal thought to the higher-frequency (α , β , γ) conscious thought (Rakovic, 1997)! It should be then pointed out that frontolimbic-amplification mechanism of pragmatic processing, in combination with the increase of dominant EEG frequency from δ to γ brainwaves during an ontogenesis (Petersen et al, 1974), implies that the mother tongue is generally memorized at low-frequency δ and θ levels (later being unconscious in adults), in contrast to second and even further languages in bilinguals and multilinguals which are memorized at high-frequency α , β , and γ levels (later being conscious in adults). This implies that second and further languages are being hardly incorporating at unconscious (automatic) levels, save only from contextual learning which enables unconscious processing of contexts - which might provide differences of the language learning in childhood and adulthood, as well as in school and in living environment (Rakovic, 1997)!

Keywords: Neural networks, brainwaves, modeling of psychological functions (learning, memorizing, consciousness, thinking, language).

The prevailing scientific paradigm considers information processing inside the central nervous system as occurring through hierarchically organized and interconnected neural networks. For instance, the visual information is firstly hierarchically processed at the level of retina (from the photoreceptory rods and cones, to the ganglion cells), to be then hierarchically proceeded within the levels of primary, secondary, and tertiary sensory and interpretatory cortical regions (all of them being additionally constituted of hierarchies of several neural networks) [1]. Interconnections within neural networks and between the neighboring neural networks in this hierarchy are achieved by synapses (one neuron having approximately 40,000 synaptic connections with neighbors), which can be excitatory or inhibitory. During the learning process, apart from the brain's hierarchy of neural networks, a significant role in global distribution and memorizing (over the whole cortex) of hierarchically processed information is played by brainwaves [2].

Along with the development of experimental techniques enabling physiological investigation of interactions of hierarchically interconnected neighboring levels of biological neural networks, significant contribution in establishing the neural network paradigm was given by theoretical breakthroughs in this field during the past two decades [3]. The potential good properties of neural networks have inspired many scientists to propose them as a solution for most problems: with sufficiently big network and adequate training, the networks could accomplish an arbitrary task, without knowing a detailed mathematical algorithm of the problem. Currently, such expectations are far from realization. To date the real solution is in finding corresponding network topology and training rules for every particular task; the past practical experiences with training of artificial neural networks imply [4] the necessity for learning not to last too long, and not to have too many hidden neurons within the network, as this gives rise to overtraining of the network and tendency to memorize the input/output vector pairs only, without generalization (learning) - with no capability to recognize some new input vector for which not being previously trained!

However, the brain consists of $\sim 10^{10}$ neurons but simultaneously it is very flexible, which clearly implies its somewhat different organization in respect to artificial neural networks. Really, although the artificial neural networks appeared as a concept of duplication of biological neural networks, many of the commercial networks do not have any essential similarity with the biological ones - which are organized as hierarchical neural networks!

HIERARCHICAL NEURAL NETWORKS VERSUS BRAINWAVES: PROSPECTS FOR THEORETICAL PSYCHOLOGY

Most of the artificial neural networks have a maximum of interconnections between functionally *nonspecialized* neurons of the neighboring layers, where every neuron of one layer is connected to all neurons of the neighboring layers (so called *massive parallelism*). However, in hierarchical neural networks interconnections between neurons of neighboring layers are much more sparse and localized.

The advantage of a *hierarchical neural network* structure is that the functionally *specialized* neurons of each layer process only a limited amount of information from the previous layer. The total global situation is then pieced together as one ascends from one hierarchical layer to the next.

Such approach requires a spectacularly smaller number of processing elements than would be required by a network with massive parallelism of interconnections between neighboring layers. It should be pointed out that hierarchical neural networks are only appropriate in those situations where the inputs to the network have low-level, intermediate-level, and high-level structures that can be consistently related to one another, as images or sounds from outdoor scenes (random data, however, do not have such structure). That is the reason why biological neural networks are organized as hierarchical networks!

A significant contribution in modeling *biological hierarchical neural networks* was given by Grossberg and his collaborators [5], working on hierarchical architecture adapted for modeling perception of illumination of a visual field, based on the experimental neuropsychological data about the visual feature extractors; the numerical simulations have shown that such a network can recognize different psychological illusions too, related to the problem of surface illumination. By introducing excitatory and inhibitory loops for intra-columnar interactions, as well as inter-columnar feedback connectivity within columnar structure of the visual cortex, Grossberg and Somers [6] predicted electroencephalographic (EEG) γ -oscillations (~40 Hz) of their hierarchical network, generated in response to steady-state-inputs. A generalization of this retinocortical model by Ögmen and his collaborators [7] produced additionally EEG α -rhythm (~10 Hz) in response to intrinsic-noise sources (in the absence of external inputs), and flash visual evoked potentials (FVEP) of various relative magnitudes and latencies (P40, N70, P100, N130, P170) in response to flash inputs. It should be pointed out that their study makes predictions for network activities that can be translated into EEG signals, providing an important missing link between single-neuron activities and the ensemble properties of the biological neural networks!

A significant contribution in modeling biological hierarchical neural networks was given by Freeman and his collaborators [8] too. By adopting a system of feedback on different hierarchical levels of the network, the neural network which reflects the dynamics of olfaction was obtained. As a result of modeling, strange attractors with multiple "wings" were obtained: the central part of attractor can be interpreted as a basal chaotic electric activity of the olfactory system (simulating the basal brainwave EEG activity without olfactory stimulus), while the wings of attractor can be interpreted as "near-limit cycles", corresponding to quasiperiodic states of the induced brainwave EP activities upon the various olfactory stimuli, implying that EEG enables brain's quicker responses upon stimuli.

Hierarchical neural networks are also a biological basis of *learning* and *memory*, as the aforementioned types of *perception* require a previous training (learning) of the network, accompanied with memorizing of the information! In the case of olfactory system, Freeman and his collaborators have proposed the following hierarchical mechanism of learning and memory [9]. Excitatory neurons are activated, strengthening their joint synapses in accordance with Hebb's rule [10]: a nerve cell assembly (NCA) is thus created comprising perhaps 1-5% of the total in the olfactory bulb. Thereafter, excitation of any portion of the NCA by receptors sensitive to a particular odor tends to activate the whole assembly.

So, it seems that *learning* in olfactory system is related to generation of corresponding activation of a local cell assembly in the olfactory bulb, while *memorizing* and *recall* is related to the whole bulb. The very activation of only a part of the odor-specific receptors results in hierarchical activation of the local cell assembly, followed by activation of the whole olfactory bulb. The similar is characteristics of the learning process in general [2]: while something is learned, information is hierarchically processed in primary, secondary, and tertiary brain areas, being afterwards spread by brainwaves over the whole cortex; however, when learning is achieved (so called habituation), the same visual stimulus can only be found in the visual system.

This also implies that brainwaves play a significant role in *distribution* of information across the whole cortex, and its *memorizing*. Of particular interest in this process is also extended reticular-thalamic activating system (ERTAS) [11], as a hierarchical system of neural networks which compares currently processed information with the one memorized in the cortex, giving priority and amplifying one piece of

information to the conscious frequency levels of α , β , and γ brainwaves; the rest of information remain nonamplified at unconscious frequency δ and θ levels (it should be stressed that the oscillator model of Ellias and Grossberg [12] really predicts EEG rhythmicity in such a way that an *increase in the input* causes an *increase in the frequency* of oscillations, and *decrease in their amplitude*, offering an unified explanation of EEG waves ranging from δ to γ). This might basically be also the mechanism of "emotional coloring" of some information, and its ascending upon the ERTAS-amplification from the lower-frequency (δ , θ) unconscious form of primordial subliminal thought to the higher-frequency (α , β , γ) conscious thought! So, it seems that there are two levels of information *coding* and *memorizing* in biological neural networks [13,14]: spatio-temporal level (responsible for spatially distributed memory, through dynamic strengthening and weakening of synapses, in accordance with Hebb's rule) and ultralowfrequency level (responsible for normally conscious and unconscious states and their interactions, through the ultralowfrequency modulation of the first level).

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Accordingly, a *thinking* process could be separated in at least two parts: first, the selection of one piece of information out of complete one processed by hierarchical structure of brain's neural networks, and its amplification to the conscious level, and second, the problem solving related to this piece of information. The first process is accompanied by emotional and verbal modulation of information by nondominant (normally right) and dominant (normally left) cerebral hemisphere, respectively [15]. The second process includes the prefrontal region and the associative secondary and tertiary cortical structures [16]. The significant role in this process can belong to brainwaves - through distribution of information across the whole cortex [2], and in transitional states of consciousness (with anticipating creative insights), and altered states of consciousness (with intense associative mixing of normally conscious and unconscious contents related to this problem, which can contribute to acceleration of the problem solving) [13,14]!

A modeling of verbal modulation of information is an important but extremely complex task, still waiting to be fully accomplished in future hierarchical neural networks. However, it seems that basic brain mechanisms responsible for organization of natural *language* are known [17]: (a) Semantic processing (which relates indicant and symbol to the sensory input from which they derive) is carried out by systems which involve the posterior "association" areas that surround the primary sensory areas; (b) Pragmatic processing (which relates sign and symbol to their user) is carried out by ERTAS-like systems which involve the frontolimbic cortical formations of the brain; (c) Syntactic processing (the arrangement of indicants and symbols) is carried out by the motor systems of the brain to which both posterior and frontal cortical formations project.

It should be then pointed out that ERTAS-like mechanism of pragmatic processing, in combination with the increase of dominant EEG frequency from δ to γ brainwaves [18] during an ontogenesis, implies that the mother tongue is generally memorized at low-frequency δ and θ levels (later being unconscious in adults), in contrast to second and even further languages in bilinguals and multilinguals which are memorized at high-frequency α , β , and γ levels (later being conscious in adults) - which then implies that second and further languages are being hardly incorporating at unconscious (automatic) levels, save only from *contextual learning* which enables unconscious processing of contexts [14]!

This might provide differences of the language learning in childhood and adulthood, as well as in school (conscious/grammatic, noncontextual), and in living environment (unconscious/nongrammatic, contextual) [14]!

REFERENCES

- [1] M.Livingstone, Art, illusion and the visual system, *Sci.Amer.*, Jan. 1988, pp. 68-75.
- [2] E.R.John, T.Yang, A.B.Brill, R.Young, and K.Ono, Double-labeled metabolic maps of memory, *Science* 233 (1986), pp. 1167-1175.
- [3] J.J.Hopfield, Neural networks and physical systems with emergent collective computational abilities, *Proc. Nat. Acad. Sci. USA* 79 (1982), pp. 2554-2558; D.Amit, *Modeling Brain Functions: The World of Attractor Neural Nets* (Cambridge Univ. Press, Cambridge, MA, 1989); H.Haken, *Synergetic Computers and Cognition: A Top-Down Approach to Neural Nets* (Springer, Berlin, 1991); K.H.Pribram, ed., *Rethinking Neural Networks: Quantum Fields and Biological Data* (Lawrence Erlbaum A., Hillsdale, NJ, 1993).
- [4] D.Hammerstrom, Working with neural networks, *Spectrum*, July 1993, pp. 46-53.

- [5] S.Grossberg, E.Mingolla, and D.Todorovic, A neural network architecture for preattentive vision, *IEEE Trans. Biomed. Engin.* 36 (1989), pp. 65-84.
- [6] S.Grossberg and D.Somers, Synchronized oscillations during cooperative feature linking in a cortical model of visual perception, *Neural Networks* 4 (1991), pp. 453-466, and references therein.
- [7] S.Azizi, H.Ogmen, and B.H.Jansen, A unified analysis of alpha rhythm, fast synchronized oscillations, and flash visual evoked potentials, *Neural Networks* 9 (1996), pp. 223-242, and references therein.
- [8] Y.Yao and W.J.Freeman, Model of Biological Pattern Recognition with spatially chaotic dynamics, *Neural Networks* 3 (1990), pp. 153-170.
- [9] C.A.Skarda and W.Freeman, EEG research of neural dynamics: Implications for models of learning and memory, in *Systems with Learning and Memory Abilities*, J.Delacour and J.C.S.Levy, eds. (North-Holland, Amsterdam, 1988), pp. 199-210.
- [10] D.Hebb, *The Organization of Behavior* (Addison-Wesley, New York, 1990).
- [11] B.J.Baars, *A Cognitive Theory of Consciousness* (Cambridge Univ., Cambridge, MA, 1988); K.R.Poper and J.C.Eccles, *The Self and Its Brain* (Springer, Berlin, 1977), Chs. E2,8.
- [12] S.A.Ellias and S.Grossberg, Pattern formation, contrast control, and oscillations in the short term memory of shunting on-center off-surround networks, *Biological Cybernetics* 20 (1975), pp. 69-98.
- [13] D.Rakovic, *Fundamentals of Biophysics* (Grosknjiga, Belgrade, 1994, 1995), Chs.5-6; and references therein.
- [14] D.Rakovic, Hierarchical neural networks and brainwaves: Towards a theory of consciousness, in Lj.Rakic, G.Kostopoulos, D.Rakovic, and Dj.Koruga, eds., *Brain & Consciousness: Proc. ECPD Workshop* (ECPD, Belgrade, 1997), pp. 189-204; and references therein.
- [15] T.H.Budzynski, Clinical applications of non-drug-induced states, in B.B.Wolman and M.Ullman, eds., *Handbook of States of Consciousness* (Van Nostrand Reinhold, New York, 1986), pp. 428-460.
- [16] A.R.Luria, *Fundamentals of Neuropsychology* (Moscow State University, Moscow, 1973), in Russian.
- [17] K.H.Pribram, *Languages of the Brain* (Brooks/Cole, Monterey, CA, 1977), 2nd ed.
- [18] I.Petersen, U.Selldwn, and O.Eeg-Olofsson, The evolution of the EEG in normal children and adolescents from 1 to 21 years, in A.Remond, ed., *Handbook of EEG and Clinical Neurophysiology*, Vol.7, Part B: *Influence on the EEG of Certain Physiological States and Other Parameters* (Elsevier, Amsterdam, 1974).