A MODEL OF ARTIFICIAL NEURONAL NETWORKS DESIGNED ACCORDING THE NATURAL NEURONAL BRAIN STRUCTURES*

T. Kolda, J. Faber, P. Svoboda, M. Dvořák[†]

Abstract: The functional structure of our new network is not preset; instead, it comes into existence in a random, stochastic manner.

The anatomical structure of our model consists of two input "neurons", hundreds up to five thousands of hidden-layer "neurons" and one output "neuron".

The proper process is based on iteration, i.e., mathematical operation governed by a set of rules, in which repetition helps to approximate the desired result.

Each iteration begins with data being introduced into the input layer to be processed in accordance with a particular algorithm in the hidden layer; it then continues with the computation of certain as yet very crude configurations of images regulated by a genetic code, and ends up with the selection of 10% of the most accomplished "offspring". The next iteration begins with the application of these new, most successful variants of the results, i.e., descendants in the continued process of image perfection. The ever new variants (descendants) of the genetic algorithm are always generated randomly. The determinist rule then only requires the choice of 10% of all the variants available (in our case 20 optimal variants out of 200).

The stochastic model is marked by a number of characteristics, e.g., the initial conditions are determined by different data dispersion variance, the evolution of the network organisation is controlled by genetic rules of a purely stochastic nature; Gaussian distribution noise proved to be the best "organiser".

Another analogy between artificial networks and neuronal structures lies in the use of time in network algorithms.

For that reason, we gave our networks organisation a kind of temporal development, i.e., rather than being instantaneous; the connection between the artificial elements and neurons consumes certain units of time per one synapse or, better to say, per one contact between the preceding and subsequent neurons.

*This study was partially supported by grant AV ČR Czech Ministry of Education No: MSM210000024 and grant Czech Academy of Sciences No: IAA21244301.

†T. Kolda, J. Faber, P. Svoboda, M. Dvořák
Joint Laboratory of System Reliability (JLSR), Department of Control Engineering and Telematics Faculty of Transportation Sciences Czech Technical University Prague, Konviktská 20, 110 00 Prague 1, Czech Republic

The latency of neurons, natural and artificial alike, is very important as it enables feedback action.

Our network becomes organised under the effect of considerable noise. Then, however, the amount of noise must subside. However, if the network evolution gets stuck in the local minimum, the amount of noise has to be increased again. While this will make the network organisation waver, it will also increase the likelihood that the crisis in the local minimum will abate and improve substantially the state of the network in its self-organisation.

Our system allows for constant state-of-the-network reading by means of establishing the network energy level, i.e., basically ascertaining progression of the network's rate of success in self-organisation. This is the principal parameter for the detection of any jam in the local minimum. It is a piece of input information for the formator algorithm which regulates the level of noise in the system.

Key words: *Time dependent artificial network, genetic algorithm, stochastic training, brain structures, parallel computation, formator – complex*

Received: June 25, 2004
Revised and accepted: August 12, 2004

1. Introduction

Our study has a dual purpose, a) to project a new efficient network of artificial neurons, the activities of which would be more like natural brain structures and b) to design a practically functioning model such as would serve as a reliable analyser and classifier of states, curves, patterns and the like. In the future we should like to go as far as modelling dynamic changes in neuronal networks such as occur in sleep, or as far as simulating higher nervous structures and functions, e.g., columns or hypercolumns as we already once did using the Simula language (Faber and Weinberger [11]).

We chose to innovate the neuronal networks by means of structural changes and new algorithms of learning and also by introducing a "finite" speed of impulse propagation including latency on artificial "neurons".

The functional structure of our new network is not preset; instead, it comes into existence in a random, stochastic manner. We were inspired by neurophysiological knowledge and mathematical models, mainly by Farley and Clark system [17].

Lion and Winter [23] and Saunders [27] used physical and mathematical modelling to show that the basic EEG alpha rhythm is very much like noise of the Gaussian distribution. Neuronal impulses or unit potentials studies in an interval histogram exhibit "noise-like" distribution even as early as the prenatal period. Crepel [4] demonstrated a Gamma III (according to Pearson) distribution of Purkinje cells even in adult rats. Bergström [3] found the interval histogram distribution dependent on age with the Poisson distribution slowly changing into the Gaussian variety and with the dispersion of interval around the mean value decreasing. The author concluded that the entropy of the unit potentials activity grows less in inverse proportion to age. Also very much like the Poisson distribution is the activity of impulses in the limbic cortex of rabbits from neonates up to three months of age – at rest and in response to sensory stimulation (Nikitina [25]). As for the cortical structure, we drew inspiration from anatomical neurophysiological discoveries made by several authors (Eccles [6], Verzeano [28], Kandel [21], Jones [19]) as well as from mathematical models, in particular, from the self-organising system devised by Farley and Clark [17].

Humans, too, were found to have a complex firing of neurons in what is a mix of reactive response in psychotests and spontaneous noise, i.e., "random firing". These phenomena were described by Halgren et al. [18] in neurons of the hippocampus and amygdala, and by Creutzfeldt et al. [5] in neurons of the temporal neocortex.

2. Definition of the Farley and Clark system

The formator or modifier is a small area of active elements (here neurons) capable of programme-controlling a vast remote area of again active elements (here neurons) in the complex. The formator sends out directions to the complex as to how, what and when to deal with and sets thresholds of excitability for the elements of the complex, sometimes supplying also "constructive noise" to the complex (see hereafter). The complex then deals with the assigned tasks making use of the data present in it partly genetically, partly as received from the sensory organs. It is as if the complex comprised two kinds of data: facts designed to be solved or considered, as well as instructions on when and how to handle the data, i.e., algorithms. In a way, this process is reminiscent of working on mathematical problems. For instance, Pythagoras's theorem $c^2 = a^2 + b^2$ can be treated in different ways, using an equation we have written about here, or geometrically, or empirically or as Thales's theorem (all triangles constructed over the diameter of a circle are right-angled) and so on. Hence, we cannot simply say that the formator will provide the algorithm for the solution (it is not fit to perform this function) while the complex provides the specific data (a, b, c sides and their values). What the formator is more likely able to supply is a design for the method of approach as mentioned above. The mathematical, geometrical solution, etc. and sophisticated implementation will be done by the cortex. This is quite obvious in the mode of thinking, especially programmistic thinking: one and the same stimulus, e.g. hearing water running during wakefulness, will provoke the right kind of perception and reaction; in the course of synchronous sleep, it may provoke a reflex dream of a river, while in paradoxical sleep the same stimulus will provoke, say, a dream of voyage on rough seas with feelings of fear.

In general, we can conceive the Farley and Clark system as applied in widely different systems, specialties, fields. In chemical processes, the function of the formator is performed by the catalyzer; in biochemistry – by enzymatic proteins; in endocrinology – by the tiny pituitary gland controlling a vast system of endocrine glands and metabolism of all tissues; in meteorology these may be eruptions in the remote Sun which we ourselves can hardly perceive, in sociology it is the government and state institutions that control a large population of the nation, and so on. The influence of the formator, e.g. government, must be appropriate, it must be neither imperative, dictatorial, nor too free such as would lead to anarchy.

The mathematical model of the formator and the complex and its computerisation were developed in the 1960s. Farley and Clark [17] designed a self-organizing cybernetic system capable of controlling and repairing itself on the basis of recognition of its own reactivity errors. The more recent artificial networks such as the neuronal systems Adaline or Madeline (Beneš [1], Nicolis et al. [24], Novák et al. [26]) and Selfridge's pandemonium were constructed along similar lines and, in addition, they already had a multilayer cortex-like structure. The Farley and Clark model has four parts: generator of signals, complex, discrimination or analytical unit, and formator or modifier. The signal generator sends impulses into the complex which is divided into four quadrants: two input ones – 01 and 02 and two output quadrants – 0+ and 0 – . All four units of the complex comprising 128 independent elements are randomly interconnected as are the 128 elements, also interconnected according to random numbers (Fig. 1).

The signal generator sends its signals alternately to the 0+ or 02 quadrants of the complex; these impulses are freely dispersed throughout the complex. The purpose of learning is that the "stimulation" of 01 should activate solely the 0+ and not the 0- quadrant. Similarly, excitation of the 02 should activate solely the 0-quadrant. The complex with the signal generator alone would have learned this over a very long time; however, the whole process of learning is greatly accelerated by the other two elements – the discrimination unit along with the formator. The discrimination unit monitors the state values of the complex and supplies information about them to the formator and to the signal generator. Apart from sending Gaussian noise to the complex, the formator sets the input and output thresholds of the elements of the complex. With the assistance of the last two members of the whole system, learning proceeds very fast and the system can soon learn the responses 01→0+ or 02→0-. Nicolis et al. [24] used not only Gaussian but also "jitter" noise which, however, not only blocked the process of learning but also disrupted the whole system organisationally; this system failed to converge to stability with higher-level organization.

These models inspired us to advance analogies with the nervous system. The complex resembles a poorly organized neonatal cortex which is only partially preformed genetically. The signal generator is nearly identical with the rhythmic thalamic generators which supply not only sensory information from external and internal environments but also send to the complex regular impulses very much like clock impulses in a microprocessor. The discrimination unit performs very much the same function as the limbic system which also detects endogenous state values of the organism and the brain, and which takes a share in motivational behaviour. And last, the most interesting part of the system, the formator is analogical to the brain-stem centers (Faber [7], [12], [14], Faber and Vladyka [9], [10]). Most of these centers are ready-made thanks to the genetic plan well before birth; they have a significant role to play in the maturation of the suprabulbar and cortical structures. E.g., the nuclei for paradoxical sleep, locus caeruleus or nucleus gigantocellularis, send out massive salvoes influencing limbic as well as neocortical structures already in the prenatal period, and, in a cyclic way, during the episodes of paradoxical sleep. Jouvet [20] specifically refers to genetic brain programming (Fig. 2).

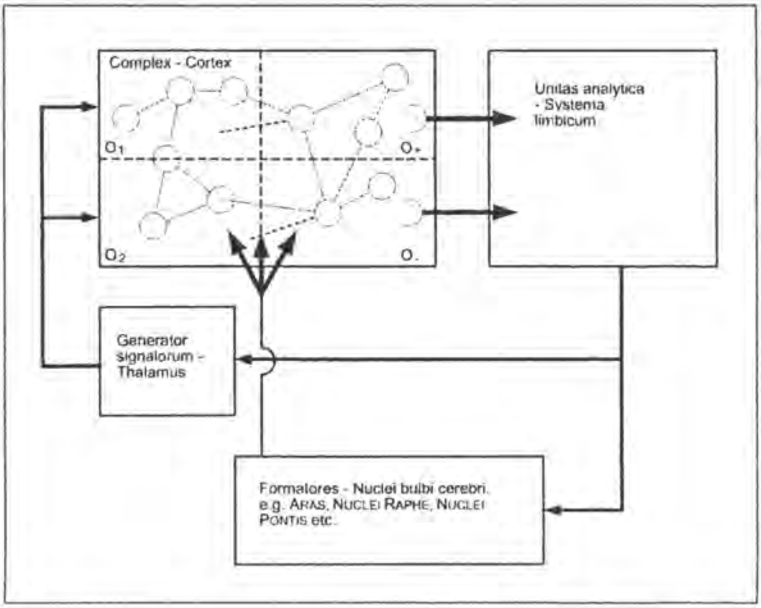

Fig. 1 *The self-organising system designed and developed by Farley and Clark consists of four main parts: complex of elements comparable with the cortex. The connection of the elements and the input thresholds of the elements are at first designed at random. The generator of signals sends alternately impulses into the 01 or 02 parts of the complex; it is analogical to the thalamus which, together with the cortex, constitutes the thalamocortical reverberation system. In keeping with the state quantities detected, the signal generator is controlled by the discrimination unit. This unit is reminiscent of the limbic system which, too, detects the "state values", i.e., the equilibrium and "composure" of the out body and mind, and "motivates" our behaviour by the results detected. The fourth member of the system, the formator, sets the thresholds of the complex elements excitability and sends Gaussian noise into the complex. The formator's activity is analogical to that of the brain-stem nuclei which, too, set the thresholds of the cortical neurons' excitability, thus switching the states of the cortext, e.g., from wakefulness to sleep, etc. The formator and complex coordination gives rise to an anatomico-physiological unit of crucial importance – FC (symbolically Farley and Clark or "faber componens" – the architect setting up the system).*

3. Our model proper

The anatomical structure of our model consists of two input "neurons", hundreds up to five thousands of hidden-layer "neurons" and one output "neuron". (Fig. 3) The number of input and output "neurons" is low rather from didactic reasons because very low numbers facilitate two-dimensional visualisation. Moreover, not even a single output "neuron" could be seen as too little if it were able to cope with a situation as complex as the decision-making process, for instance, whether a freshly analysed EEG curve without typical epileptic graphoelements came from

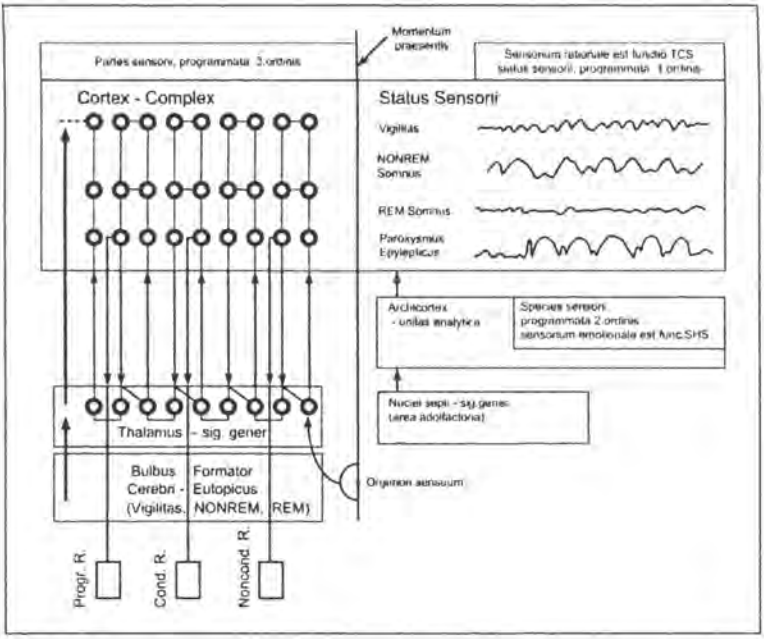

Fig. 2 *Brain-stem nuclei of non-specific afferentation influence in a crucial way cortical activity already before birth, simply on the basis of the genetic plan, thus giving rise to* states, *programmes of the 1st order: vigilance, NONREM and REM sleep, as early as two months before the child is born. These are states of consciousness. In the postnatal period, these genetic effects are joined by exogenous influences taken in by sensory organs, thus giving rise to programmes of the 2nd order called* types of consciousness: *processes of attachment, emotions, states focussed attention or general attention, etc. Simultaneously with the thalamocortical system, the septohippocampal system too, goes on maturing. In around one year of life, specifically human programmes, i.e., programmes of the 3rd order, start developing in what we call* parts of consciousness. *At that time, the cortext shows signs of anatomical and physiological differentiation; speech and abstract thought begin developing. Formators for the cortex are in the brain stem; formators for the archicortex are represented by septal nuclei, or rather the area adolfactoria in homo sapiens.*

an epileptic (yes) or a healthy person (no), which is exactly where a single binary number would do.

Neuron: $N \in \{\xi\}$, *where* ξ *is a complete set of neuron parameters (weights, transfer function, threshold, etc.).*

Our model of an artificial neuronal network is not based on conventional "back-propagation" algorithms as these fall short of introducing noise into an organisation or involving hundreds of elements; (Novák et al. [26]). Networks organised by the back-propagation mechanism have, on the whole, simple processes in each partic-

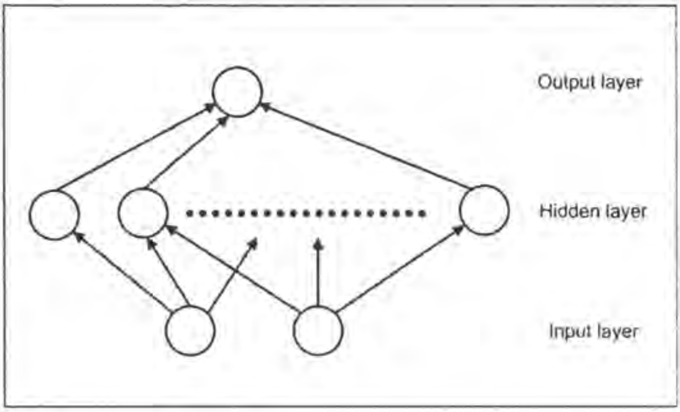

Fig. 3 *Morphological structure of our model consisting of three layers (input, hidden, output).*

ular iteration except that large numbers of such iterations are necessary, e.g., tens up to hundreds of thousands.

In our networks, each iteration is complex just because of the presence of noise, but it is very effective, and that is why the process of learning in our network takes a much faster course requiring tens or hundreds of iterations.

Input training set: $P_I \in R^n$

Output training set: $P_O \in R^m$

Result set: $P_R \in R^m$

Neural network state: $S \in \{N^n\}$, *where n is a count of the neurons in network*

Transfer function of the neural network input layer:

$Y = F(P_I, \xi)$, *where* P_I *is a network input set (1)*

Transfer function of the neural network output layer:

$P_R = F(x, \xi)$, where x are neuron's inputs (2)

Our presented network realises a process, in which it learns to create and recognize geometrical figures such as a circle or square, but also more complex figures such as an empty-centre circle, a kind of annular ring or lagoon. The last-named figure is difficult to learn for an artificial network since no continuum of the shape has been preserved here; instead, there is a recurrent interruption, as will be easy to show if we imagine this "lagoon" as intersected by a straight line (Fig. 9).

The process proper is based on iteration, i.e., mathematical operation governed by a set of rules, in which repetition helps to approximate the desired result (Fig. 4).

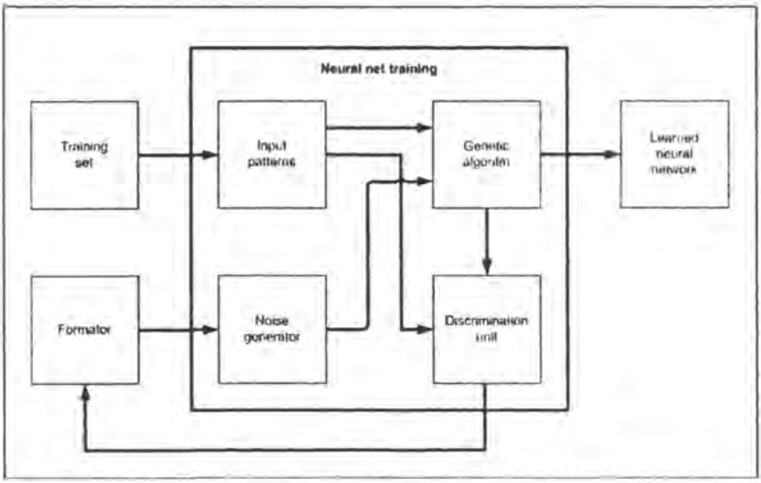

Fig. 4 *Neural network training based on genetic algorithm.*

Iteration I: $S(n) = F(S(n-1), f(E))$, *where F is the modification function and f(E) is the formator function that regulates noise* (3)

Level of system energy: $E = \sum_{i=1}^{N} f(P_{O\,i}, P_{R\,i})$, *where N is a count of traning sets and f is a metric function* (4)

Each iteration begins with data introduced into the input layer to be processed in accordance with a particular algorithm in the hidden layer; it then continues with the computation of certain as yet very crude configurations of images created by a genetic algorithm, and ends up with the selection of 10% of the most accomplished "offspring". The next iteration begins with the application of these new, most successful variants of the results, i.e., descendants in the continued process of image perfection. All the new variants (descendants) of the genetic algorithm are always generated randomly. The deterministic rule then only requires the choice of 10% of all the variants available (in our case 20 optimal variants out of 200).

Genetic algorithm – modification function F

1) *Take the current state S of the neural network. From S compute the n number of children by randomizing the parameters ξ with noise amount f(E).*

2) *Based on the energy E choose best x percent from computed children.*

3) *Create new state S. If energy is below our goal, end the process. Otherwise go to step 1.*

The algorithm change rested in the possibility to involve up to thousands of artificial neurons in a single layer.

In other words, a genetic mechanism was employed to create a functional state of the network (Fig. 5). Similarly as in living organisms, it is a case of indicating a certain direction of functional structures development rather than of total genetic predestination. This mechanism also enables specific adjustment of the initial conditions, an option of importance for subsequent uses of the network as a specialised classifier for some particular purpose. These initial conditions will be different for the shape reading functions, different again for the reading of curves or for the classification of diverse symptoms in differential diagnoses, etc.

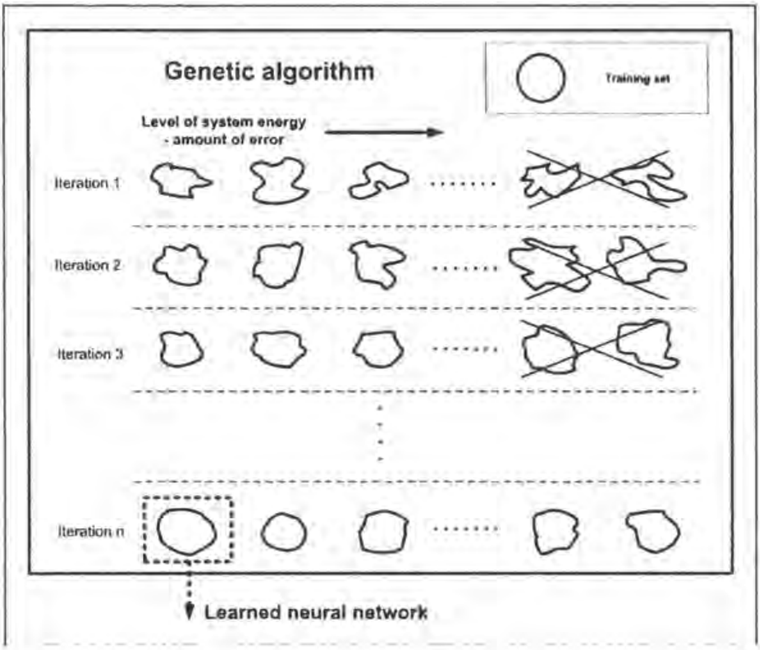

Fig. 5 *Example of learning process with genetic algorithm.*

The stochastic model is marked by a number of characteristics, e.g. the initial conditions are determined by different data dispersion variance, the evolution of the network organisation is regulated by genetic rules of a purely stochastic nature; Gaussian distribution noise proved to be the best "organiser". (Just for illustration see Fig. 6.)

We also tried out different characters of noise, e.g. a uniform one, in which all data exhibit the same probability of incidence. There, too, the network became organised with success, albeit at a slower rate.

This new stochastical organisation of the network of artificial neurons makes it possible to perform computations in parallel in a network of computers, thus substantially speeding up the process of computation.

Another analogy between artificial networks and neuronal structures lies in the mode of time. According to Laufberger [22], life is a complex of fixed cyclic

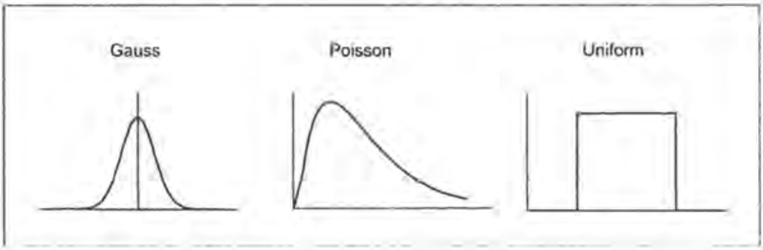

Fig. 6 *Examples of different statistical distributions.*

enzymatic reactions. As early as 1938, Berger [2] found electric rhythms in the brain and gave them the names of alpha (8-13 Hz) and beta (14-30 Hz). All of us perceive time consciously and unconsciously. For that reason, we gave our networks organisation a kind of temporal development, i.e. rather than being instantaneous, the connection between the artificial elements and neurons consumes certain units of time per one synapse or, better to say, per one contact between the preceding and subsequent neurons. Next, each element has a particular latency between the stimulation (signal) at the input and the response (signal) at the output. Neurologically speaking, this is a complex process which consists of the reception of impulses (signals) at hundreds up to thousands of synapses (points of interneuronal connection), the threshold of irritation on the neuronal membrane and the impulse output from the neuron, a process taking place at the axon hillock (a special organelle of the neuron).

The latency of neurons, natural and artificial alike, is very important as it enables feedback action. Indeed, a negative feedback can be realised by a great prolongation of this latency.

Systems making no use of latency are incapable of organisation, convergence toward a state of stability (Votruba [29]).

Getting stuck in the local minimum is a frequent impediment in the organisation of networks. At first, our network becomes organised under the effect of considerable noise. Then, however, the amount of noise must subside (Fig. 7).

However, if the network evolution gets stuck in the local minimum, the amount of noise has to be increased again. While this makes the network organisation waver, it will also increase the likelihood that the crisis in the local minimum will abate and improve substantially the state of the network in its self-organisation. In other words, after a temporary "deliberate" increase, the level of entropy will decrease markedly (Fig. 8).

Introduced into the network algorithm was the feedback for automatic detection of the organisation's jam in a local minimum. A situation like that is dealt with by raising the level of Gaussian noise as already mentioned before. With the functional structure of the network jammed in an intricate situation the system might well repeatedly lapse into the same local minima. For that reason, we devise and realise their registration, i.e. their "topology" and storage in memory.

For constant state-of-the-network, our system allows reading by means of establishing the network energy level, i.e. basically ascertaining progression of the network's rate of success in self-organisation. This is the principal parameter for

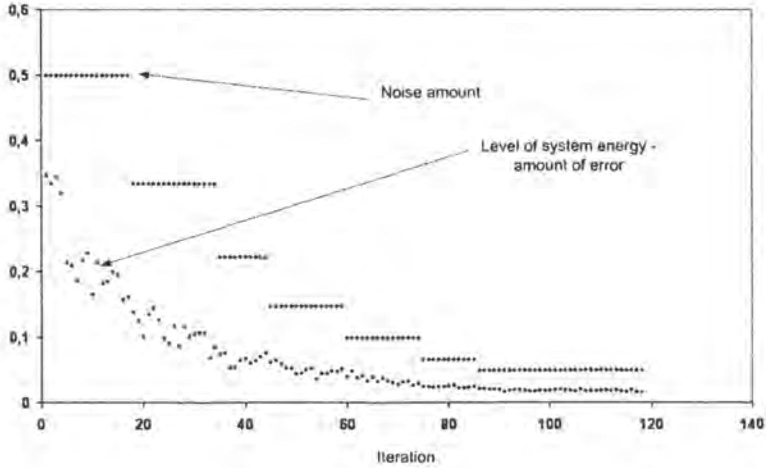

Fig. 7 *Occurence of square picture learning by help of noise.*

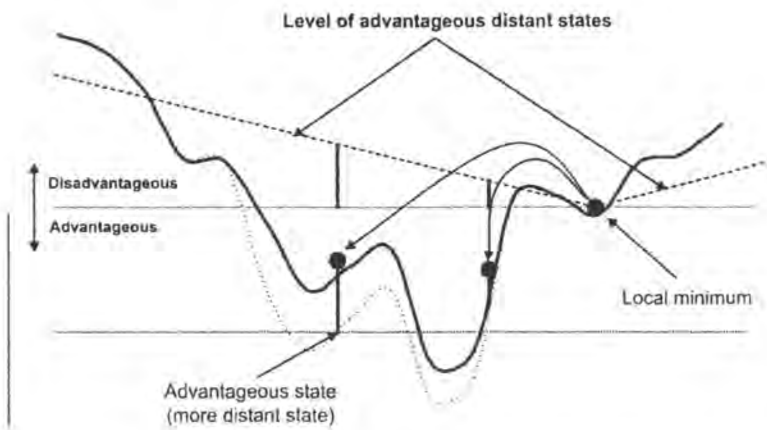

Fig. 8 *Employment of noise for escape of the system from stuck in the local minimum.*

the detection of any jam in the local minimum. It is a piece of input information for the algorithm which regulates the level of noise in the system.

For examples of stochastic network application to image classification see (Fig. 9).

4. Conclusion

Our model is, to a degree, reminiscent of one of the first cybernetic self-organising systems designed by Farley and Clark, which, however, is very much different from the later "stratified" neuronal networks. All the same, we see it as very important and are in the habit of reusing it since, more than other systems, it reminds us of

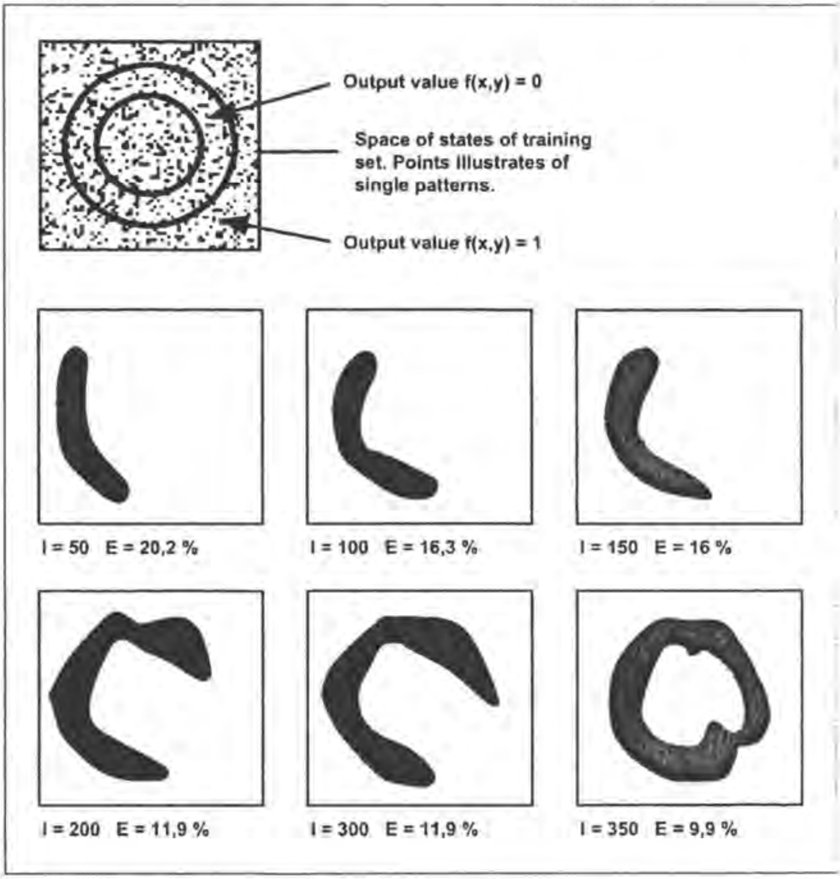

Fig. 9 *Occurence of geometrical picture learning (I – Number of Iteration, E – system energy).*

the essential structures in the brain (CNS = central nervous system), as already described. The following are analogies between the systems under study: Farley and Clark (FC), our present-day stochastic model (SM) and the brain system (BS or CNS).

The FC generator of signals alternately sends out signals to the O1 or O2 parts of the complex of elements, and is controlled by an analytical unit. In our SM system, this part is played by the two input "neurons" designed, in the future, to represent the input into, say, the "perceptron" which can read and classify any curve (seismogram, electrocardiogram, tachogram, electroencephalogram, etc.). In the CNS this is the thalamus conducting impulses from the senses to the brain cortex (neocortex).

The complex of 128 elements randomly interconnected in the FC model is in our SM system represented by a hidden layer comprising the above-mentioned hundreds up to thousands of "neurons"; this is the site of the actual process of learning and visualisation of, e.g. geometrical figures. In the brain system (CNS) we refer to the six-layer structure of the neocortex responsible for the execution of all phatic (speech), cognitive and logical functions.

The discriminating or analytical unit is designed to analyse the states of the model and to send the relevant quantities to the signal generator and to the formator in the FC system. In our own model, this is an algorithm for the calculation of the energy levels of the actual state of the network, precisely estimating how successful the network organisation is. In the CNS, a similar function is performed by the limbic system.

The formator or modifier in the FC system sets the thresholds of irritation of the elements of the complex, and sends Gaussian noise into the complex. In our model, this is an algorithm representing part of the feedback (between the state of the organisation and its hidden layer output). This state is expressed in the energy level and/or in being stuck in the local minimum. This situation stimulates an increase in Gaussian noise which, in turn, enables escaping from the local minimum and, ultimately, to increase the rate of success of the hidden layer organisation. In the CNS, were refer to what are known as modulatory humorergic afferent non-specific systems of the brain stem or an epileptic focus (Faber [7], [16], Faber et al. [9]). (See Fig. 1 and 2.)

We also plan to introduce collateral ties or horizontal connections of "excitatory and inhibitory" feedbacks in a single layer. For greater similarity with biological systems we intend to develop networks of up to 6 layers as in the mammalian neocortex. At the same time, we expect the layers to have similar functions: input or afferentation of signals from the input layer (thalamic nuclei) into the 4th hidden layer, from there the signals disperse into hidden layers 3 to 5; conceivable intracortical circulation between hidden layers 2 to 5 and, possibly, the processed data output from layer 6 into the output elements, i.e., the thalamus or some other cortical motor and imaging systems. Hidden layers 1 and 2 would then serve as mediators of stimuli between the formator and this neocortical six-layer structure so that it would set and occasionally alter the thresholds of irritation of some of the neocortical elements, in particular mainly hidden layers 3 and 5. The present neurophysiological knowledge provides also other possibilities for intracortical and thalamocortical interactions and data processing.

References

[1] Beneš J.: Kybernetické systémy s automatickou organizací. Academia. Praha, 1966, p. 174. (In Czech)

[2] Berger H.: Das Elektrenkephalogramm des Menschen. Nova Acta Leopoldina. Halle/Saale, 1938, p. 139.

[3] Bergström R. N.: Development of EEG and unit electrical activity of the brain during ontogeny. In: Ontogenesis of the brain 1968, Charles University. Ed: S. Trojan, F. Šťastný.

[4] Crepel F.: Maturation of the Cerebellar Purkinje Cells. Exp. Brain Res. 1972, **14**, pp. 463-471.

[5] Creutzfeldt O., Ojeman G., Lettich E.: Neuronal activity in the human lateral temporal lobe. Exp. Brain Res., **77**, 1989, pp. 451-475.

[6] Eccles J. C.: The understanding of the brain. McGraw-Hill Book Comapany., New York, 1973.

[7] Faber J.: Vigilance, sleep, petit mal and EEG as manifestations of programmed brain regulation. Acta Univ. Carol. Med., Monogr. LXXXVII, Praha, 1978.

[8] Faber J., Vladyka V., Dušek J., Taichmanová Z.: Vigilita, NONREM a REM spánek a epileptický záchvat. Čtyři stavy neboli systémy formátor-komplex. Čas. Lék. es., **120**, 1981, pp. 1338-1342. (In Czech)

[9] Faber J., Vladyka V.: Nocturnal sleep stereo-EEG and polygraphy in epileptics. Acta Univ. Carol. Med., Monogr. CVIII, Praha, 1984.

[10] Faber J., Vladyka V.: Epileptogenesis and "Psychosogenesis", antithesis or synthesis? Acta Univ. Carol. Med., **33**, 1987, pp. 245-312.

[11] Faber J., Weinberger J.: Thalamocortical reverberation circuit simulation using the Simula Language. Acta Univ. Carol. Med., **34**, 1988, pp. 149-248.

[12] Faber J.: Epilepsie a epileptosy. Maxdorf – Jesenius, Praha, 1995, p. 271. (In Czech)

[13] Faber J., Vladyka V., Dufková D. et al.: "Epileptosis" - a syndrome or useless speculation? Sborn. lék., **97**, 1996, pp. 71-95.

[14] Faber J.: Temporální epilepsie a vědomí. Triton, Praha, 1998, s. 212. (In Czech)

[15] Faber J., Šrutová L., Pilařová M. et al.: EEG spectrum as information carrier. Sborn. lék., **100**, 1999, pp. 191-204.

[16] Faber J.: Isagogé to non-linear dynamics of formators and complexes in the CNS. Acta Univ. Carol. Med., Monogr. CXLIX, Praha, 2003, p. 125.

[17] Farley B. G., Clark W. A.: Simulation of self-organizing systems by digital computer. Trans. IRE 1954, PGIT-4, pp. 76-84.

[18] Halgren E., Thomas L. B., Crandall P. H.: Activity of human hippocampal formation and amygdala neurons during memory testing. Electroenceph. Clin. Neurophysiol., **45**, 1978, pp. 585-601.

[19] Jones E. G.: Thalamic circuitry and thalamocortical synchrony. Philosophical transactions of the Royal Society. Biological Sciences, **357**, 2002, pp. 1659-1674.

[20] Jouvet M.: L'histoire naturelle du réve. Exposé en la séance du lundi 24 novembre 1975. Académie des Sciences, Institut de France, Paris, **9**, 1976.

[21] Kandel E. R.: Processing of Form and Movement in the Visual System. In: Kandel E. R., Schwartz J. H.: Principles of neural science. Elsevier, Amsterdam, 1985, p. 981.

[22] Laufberger V.: Impuls theory. Nákladem Spolku českých lékařů. Praha, 1947, p. 238. (In Czech)

[23] Lion K. S., Winter D. F.: A method for the discrimination between signal and random noise of electrobiological potentials. Electroenceph. clin. Neurophysiol., **5**, 1953, pp. 109-111.

[24] Nicolis J. S., Protonotarios E., Lianos E.: Some view on the role of noise in "self" – organizing systems. Biol. Cybernetics, **17**, 1975, pp. 183-193.

[25] Nikitina G. M.: General organising principles of the neuronal discharge activity of limbic structures in early ontogenesis. In: Ontogenesis of the brain. Universita Karlova, S. Trojan, F. Šťastný, (Eds.). Praha, **3**, 1980, pp. 579-587.

[26] Novák M. et al.: The artificial neuronal nets, theory and praxis. C. H. Beck, Praha, 1998, p. 382. (In Czech)

[27] Saunders M. G.: Amplitude probability density studies on alpha and alpha-like patterns. Electroenceph. clin. neurophysiol., **15**, 1963, pp. 761-767.

[28] Verzeano M.: The activity of neuronal networks in memory consolidation, p. 75-97. In: Neurobiology of sleep and memory. R. R. Drucker-Colín, J. L. McGaugh (Eds.). Academic Press, New York, 1977, p. 456.

[29] Votruba Z.: System analysis lectures of ČVUT, Praha, 1996. (In Czech)