

THE NEURAL NETWORK ENVIRONMENTAL MODEL AND SOFTWARE

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Abstract. The principles of a neural network environmental model are proposed. The principles are universal and can use different neural network architectures. Such a model is self-organizing, it can operate in both regimes with and without a teacher. It codes information about objects, their features, the actions operating in an environment, analyzes concrete situations. There are functions for making an action plan, for action control. The goal of the model is given from an external site. The model has more than sixteen active regimes. The neural network environmental model is fulfilled in software and hardware tools.

Key words: neural network, environmental model, self-organizing.

1. Introduction. The problems of spatiotemporal pattern interpretation are of particular importance in the theoretical and practical questions of neural networks and neurocomputers. These questions are widely considered in works by Grossberg (1969a, b), Hecht-Nielson (1987). Also such a type of neural networks is applied to the analysis and recognition of temporal variable signals.

Another neural network application field, close to the ap-

proach proposed by us, is realization of artificial intelligence functions in the sense of creation of semantic networks and knowledge bases (Hirai, Ma, 1990; Yu and coworkers 1990).

The proposed idea is partly connected with PERT system application to the formation of knowledge bases introducing the factor of action, for example in works by Ignasyak (1977), Turner (1976). However the classical execution of this method does not allow to fulfil the generalization of objects, their features, actions and also self-organizing procedures of systems, the organization of an associative memory because the PERT system has rather limited possibilities.

The proposed neural network model allows to describe and to store associatively objects and their features, to classify the objects, to recognize them according to the sense of features, to fulfil actions by varying the features in a state evolution of a complex spatiotemporal network. This neural network becomes not only an interpreter of an environment surrounding a man but it also models the transformations of objects and their features, making the perception of an environment by a man easier.

2. The environmental model. Any system operates in a corresponding environment which can be described in the following way. There exists in an environment a set of objects $\{A_1, A_2, \dots, A_i, \dots, A_N\}$. The object A_i is characterized by a vector of features \vec{x}_i , i.e. $A_i \sim \vec{x}_i$, where $\vec{x}_i \in X^{n_x}$ and X^{n_x} is the vector space of measure n_x . Accepting instead of $A_i \sim \vec{x}_i$ a short notation $A_i(\vec{x}_i)$, we state that the object $A(\vec{x})$ is ascribed to the object $A_i(\vec{x}_i)$, if the distance between the binary vectors \vec{x} and \vec{x}_i is Xeming's or another measure. If satisfies the condition

$$d(\vec{x}_i, \vec{x}) \leq d_i^{(A)}, \quad (1)$$

where $d_i^{(A)}$ is a fixed distance in the environment of the vector \vec{x} of features.

If condition (1) is not satisfied but there exists the inequality

$$d(\vec{x}_i, \vec{x}) \leq d_i^{(B)}, \quad (2)$$

where $d_i^{(B)} > d_i^{(A)}$, the object can be ascribed to the set B , and the set A will become a subset, i.e. $A \subset B \subset C$, etc. (E.g.: patients – cardiac patients – ischemic patients; tree – pine – plank, etc.). The objects can belong to different subsets. One or another action E can take place in a system environment. On its basis the object transformation

$$A_k(\vec{x}_k) = E_1(A_i(\vec{x}_i)) \quad (3)$$

or a change of the features of the object

$$A_i(\vec{x}_k) = E_2(A_i(\vec{x}_i)) \quad (4)$$

take place.

Depending on the action the object can change (3) or it can change its features (4). The whole of transformations makes up a set $E = \{E_1(\Delta\vec{x}_1), E_2(\Delta\vec{x}_2), \dots, E_i(\Delta\vec{x}_i), \dots, E_N(\Delta\vec{x}_N)\}$ where $\Delta\vec{x}_i$ is the changed vector of the i th object features. E can have subsets, e.g., V and W , which can overlap, i.e. $V \cap W \neq \emptyset$, where \emptyset is an empty set.

An environmental model may be conveniently represented in a space of features. Then the object $A_i(\vec{x}_i)$ at $\vec{x}_i = (x_{i1}, x_{i2}, \dots, x_{iL})$ can be represented as the point of the mode of vector \vec{x}_i . The conditions (1) and (2) will correspond to the environmental point or zone (basin) of attraction (Fig. 1). An action is represented by a vector of changed features, and the result is expressed by a vector of features, which, taking into account the allowed shift of a transformation direction θ , is written

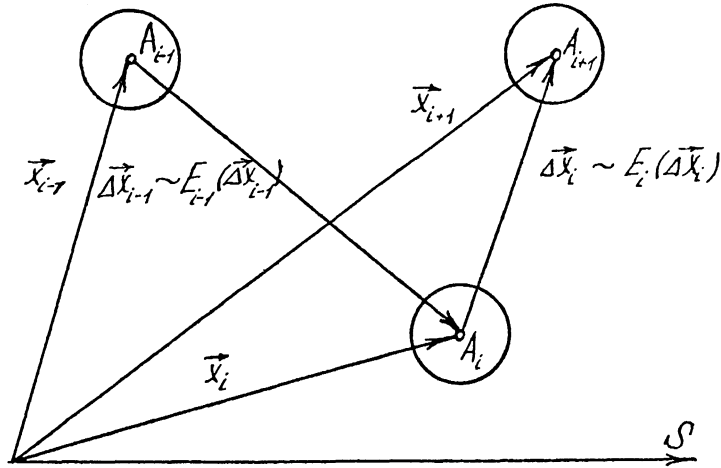


Fig. 1. Geometrical representation of object transformations (S is the base of an account).

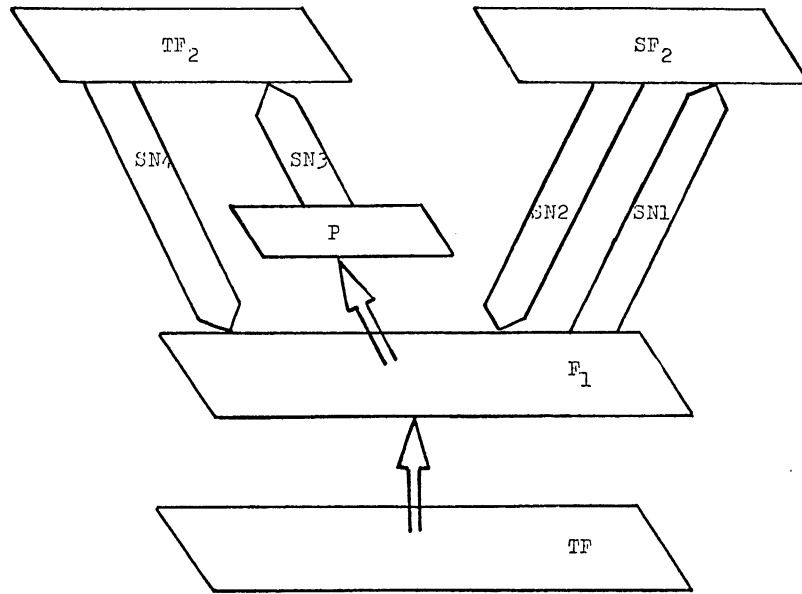
$$\vec{x}_{i+1} = \vec{x}_i + \Delta \vec{x}_i + \vec{\theta}. \quad (5)$$

Such are fundamental principles and the contents of creation of a general environmental model.

3. The architecture of a neural network. A neural network is proposed for modelling the processes taking place in the environment of systems, in whose phase space (coordinates of spaces – the states of neurons) coded and transformed information corresponds or is adequate to the transformation of features of the described (Section 2).

The architecture of the neural network is nonhomogeneous, i.e. it is composed of different structures of subnetworks whose functions can be defined in common sense in the following way:

a) Learning of the network. A pattern \vec{x} and a network response \vec{y} are sent to the input and output of the network, respectively. Modifying the inner network structure via weight matrices an associative connection $\vec{x} \rightarrow \vec{y}$ is created.



DESIGNATIONS:

- SN1, SN2, SN3, SN4 – double layer subnetworks;
- F₁ – layer of features;
- TF – aim layer;
- P – differential layer;
- SF₂ – layer of space information;
- TF₂ – layer of temporal information.

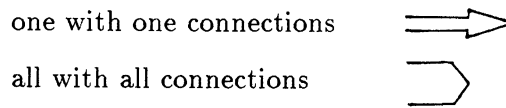


Fig. 2. Architecture of neural network environmental model.

b) Recognition. A pattern \vec{z} is given to the input of the network. The equalization of the pattern \vec{x} is fulfilled evaluating the distance $d(\vec{x}, \vec{z})$ in the accepted measure (the

measure depends on the network model chosen). If

$$d(\vec{x}, \vec{z}) \leq d(\vec{y}) \quad (6)$$

the output of the network yields a vector \vec{y} , i.e. a recognition is fulfilled.

The architecture of the neural network of an environmental model is represented in Figure 2. The network consists of four two-forward connected and double-layer subnetworks SN1, SN2, SN3, SN4. The input patterns and responses of subnetworks are coded in three basic neural layers: layer of features (F_1), space information (SF_2), temporal information (TF_2) and TF, P . The TF layer serves to set the aim (the state which the system has to achieve) of the system. The P layer yields the temporal part of information, i.e. it fulfills the differential calculus of different function in time.

The phase space coordinates to the neural states $S_1^{(F_1)}$, $S_2^{(F_1)}$, ..., $S_i^{(F_1)}$, ..., $S_N^{(F_1)}$ of layer F_1 . The layer SF_2 and subnetworks SN1, SN2 belong to the space information belong to the temporal information channel.

These channel are meant to control the dynamics of layer F_1 .

In a general case any subnetwork fulfills the function (without a transitional period)

$$\vec{S}^{(out)} = G(\vec{S}^{(inp)}, \hat{T}, \vec{u}), \quad (7)$$

where $\vec{S}^{(inp)}$, $\vec{S}^{(out)}$ are input and output state vectors of subnetworks, respectively, \hat{T} is the weight matrix constant in time, \vec{u} is the vigilance vector of a subnetwork (the component u_i of \vec{u} defines the size of basin attraction of the i th category; the larger u_i , the larger the basin).

By analogy, expression (7) can be written for a separate neuron:

$$S_i^{(out)} = g(\vec{S}^{(inp)}, \hat{T}, u_i). \quad (8)$$

Then for separate subnetworks SF_2 , TF_2 and F_1 for the i th neuron there exist the following dynamical equations:

$$C^{(SF_2)} \frac{dS_i^{(SF_2)}(t)}{dt} = -A_1 S_i^{(SF_2)}(t) + g_1(\vec{S}^{(F_1)}(t), \hat{T}^{(1)}, u_{1i}) \quad (9)$$

$$C^{(TF_2)} \frac{dS_i^{(TF_2)}(t)}{dt} = -A_2 S_i^{(TF_2)}(t) + g_2(\vec{S}^{(P)}(t), \hat{T}^{(2)}, u_{2i}) \quad (10)$$

$$C^{(F_1)} \frac{dS_i^{(F_1)}(t)}{dt} = -A_3 S_i^{(F_1)}(t) + B S_i^{(TF)}(t) + g_3(\vec{S}^{(SF_2)}(t), \hat{T}^{(3)}, u_{3i}) + C f(S_i^{(F_1)}(t)) \times g_4(\vec{S}^{(TF_2)}(t), \hat{T}^{(4)}, u_{4i}). \quad (11)$$

There $C^{(SF_2)}$, $C^{(TF_2)}$ and $C^{(F_1)}$ are temporal constants, $S_i^{(\omega)}$ is the output signal of the i th neuron of the ω th layer, $f(S_i^{(F_1)}(t))$ is a positive feedback signal in the i th neuron, A_1 , A_2 , A_3 , B and C are constants.

Equations (9), (10) are obvious. The second right member of equation (11) reflects the effect of TF layer (the neurons of F_1 and TF layers are joined one with one), the third member – the effect of SF_2 , the fourth member – the effect of TF_2 . The TF_2 layer signal to permits or forbids evolution of F_1 layer.

The evolution is permitted if

$$g_{40} = g_4(\vec{S}^{(TF_2)}(t), \hat{T}^{(4)}, u_{4i}) = 0$$

and if forbidden if $g_{40} \neq 0$. It is achieved because the signs of $S_i^{(F_1)}(t)$ and $\frac{dS_i^{(F_1)}(t)}{dt}$ are the same. The evolution of the i th neuron stops after the saturation point of a sigmoid function has been achieved.

These conditions are satisfied if

$$f(S_i^{(F_1)}(t)) = kS_i^{(F_1)}(t),$$

where k is a positive constant and $k \gg 1$. The constant k is chosen according to the condition

$$f(S_i^{(F_1)}(t)) \cdot g_{40} > I_{\max}^{(TF)} + I_{\max}^{(SF_2)},$$

where $I_{\max}^{(TF)}$, $I_{\max}^{(SF_2)}$ are maximum effects of layers TF , SF_2 on layer F_1 .

Thus the environmental model is an automatically gain-controlled feedback multilayer neural network.

4. Neural network algorithm of action and regimes. The initial state $\vec{S}^{(F_1)}$ of the neural network layer F_1 has been given at the beginning of the work of the environmental model. $S^{(F_1)}$ can be given in three ways:

1. The state left from the earlier work of the network.
2. The state set by a collection of features directly to the layer F_1 .
3. The state formed in the layer SF_2 through an association $\vec{S}^{(SF_2)} \rightarrow \vec{S}^{(F_1)}$.

A combination of these ways is possible.

The aim of the neural network work is also given. A collection of features $S^{(TF)}$ in the layer TF , the object $\vec{S}^{(TF_2)}$ in the layer SF_2 (through the association $\vec{S}^{(SF_2)} \rightarrow \vec{S}^{(TF)}$) or the action $\vec{S}^{(TF_2)}$ (in this case the vector $\vec{S}^{(TF)} = -\vec{S}^{(F_1)}$ is established) can be aims.

As the states of the layer TF are invariable, the vector $\vec{S}^{(F_1)}$ evolves to the direction of the vector $\vec{S}^{(TF)}$ making the state $\vec{S}^{(P)}$ in layer P . If the vector $\vec{S}^{(P)}$ in the sense of inequality (6) is similar to any action known by the system, this evolution is permitted. In the opposite case the evolution is forbidden and the direction of evolution in the layer F_1 changes. The process develops till the permitted direction of the evolution is found.

A variant is possible when for the evolution from $\vec{S}^{(F_1)}$ to $\vec{S}^{(TF)}$ there will not appear a proper action. In this case the neural network can consequently perform several actions.

Thus the system can make up the plan of action, i.e. to make a succession of actions enabling to achieve the aim $\vec{S}^{(TF)}$.

Suppose the neurons of the layer F_1 are strongly connected with the environment, then $\vec{S}^{(F_1)}$ can evolve only when the state of the environment changes properly. If the neurons of layer TF_2 will be connected with effectors, then such a system, according to the algorithm mentioned above, will be able to fulfill control functions.

For different subnetworks a self-organizing algorithm and the software (Garliauskas and Malickas, 1990, 1991) were used. The environmental model can operate in a dialogue regime in which the names of objects, features, and a possibility of action fulfilling can be introduced. The neural network basing on the collection of concepts enables us to find the right succession of actions passing from the given state to the given aim.

It should be noted that the larger the neural network, the more difficult it is chosen for objects their coordinates adequate for the environment in the phase space. This is connected with a subjective perception of the environment by man. This problem could be solved changing the scheme of information introduction "environment – man – neural net-

work" by scheme "environment - neural network", using the mentioned self-organizing algorithm of network and information sensing elements in the environment.

5. Hardware implementations. The multilevel environmental neural network, named NEUROLIT, is constructed in the form of a co-processor board for IBM PC AT. The NEUROLIT consists of processing elements memory chips, controllers and other blocks. The standard microprocessor CPU chips on the board take care of overall control and data routing.

Eight microprocessors Intel 8088, memory chips of 2M byte capacity, logic matrix chip, controllers are located on the board of NEUROLIT. NEUROLIT is universal and can perform the modelling of neural networks having about 500 thousand interconnections and 200 thousand neural elements (in binary case 4 million and 1,6 million ones, respectively). The speed of encoding is 80-100 times higher than that with the help of IBM PC AT.

6. Conclusions. In this paper we have proposed the original neural network environmental model based on the multilevel structure. It allows to describe and to store associatively objects and their features, to classify the objects, to recognize them according to the sense of features. For different subnetworks of the model a self-organizing algorithm and software were created. The hardware implementations of the multilevel environmental neural network, as NEUROLIT is constructed.

A whole complex of software consisting of the high level language, the neural algorithm library and the low level language for fulfilling massive parallel operations will be created for the concrete multilevel environmental neural network model or other neural network architectures.

REFERENCES

- Garliauskas, A. (1990). Self-organizing nonsymmetrical algorithm and nonlinear synaptic model of neural networks. In *Proceedings of the International Neural Network Conference*, Vol.2. Kluwer Ac. Publ., Dordrecht-Boston-London. pp. 679.
- Garliauskas, A., and A.Malickas (1991). Investigation of self-organizing model and self-learning algorithms of neural networks. In *Proceeding of Workshop Neurocomputers and Attention*,. Pushchino, USSR (to appear).
- Grossberg, S. (1969). On learning of spatiotemporal patterns by networks with ordered sensory and motor components. *Studies in Applied Mathematics*, **48**, 105-132.
- Grossberg, S. (1969). Some network that can learn, remember, and reproduce any number of complicated space-time patterns. *Journal of Mathematics and Mechanics*, **19**, 53-91.
- Hecht-Nielsen, R. (1987). Nearest matched filter classification of spatiotemporal patterns. *Applied optics*, **26**(10), 1892-1899.
- Hirai, Y., and Q.Ma (1990). Implementing semantic networks in an electronic neural network. In *Proceedings of the International Neural Network Conference*, Vol.2. Kluwer Ac. Publ., Dordrecht-Boston-London. pp. 639-642.
- Ignasyak, E. (1977). Methods of a graph theory in network planning. In *Primenenie issledovanija operatsij v ekonomike*, Ekonomika, Moscow. pp. 265-287. (in Russian).
- Turner, D. (1976). *Probability, Statistics and Research Operations*. Statistika, Moscow. 432pp. (in Russian).
- Yu, H., Z.Xianjun, Y.Yizheng and L.Zhongrong (1990). Knowledge acquisition and reasoning based on neural network the research of a bridge bidding system. In *Proceedings of the International Neural Network Conference*, Vol.1. Kluwer Ac. Publ., Dordrecht-Boston-London. pp. 416-424.

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