THE CONCEPT OF A NEURAL INTUITIVE PREDICTION MODEL

Henryk Piech, Aleksandra Ptak, Dariusz Leks

Institute of Mathematics and Computer Science, Czestochowa University of Technology

Abstract. For the modeling of multi-parameter and intercorrelated phenomena, a spatial neural network with mutual connections of neurons (Fig. 1) can be used.

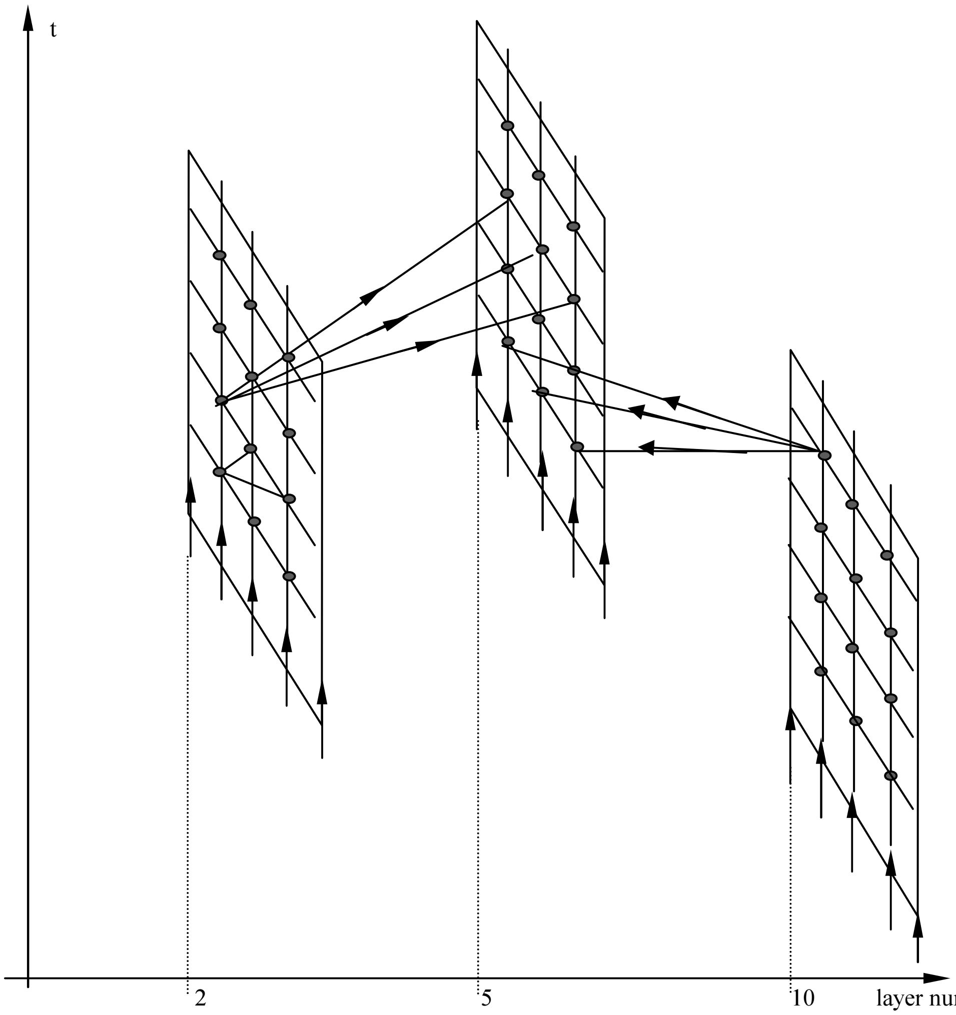

Fig. 1. Spatial structure of a neural network with mutual inter-layer (interplanar) connections

The prediction of complex situations can be based on forecasts which are usually related to phenomena with a low dynamism of progress and a high predictability, or on intuitive mechanisms. The prediction of phenomena with a large parametric range, a high rate of their variability and a considerable level of unpredictability is distinguished by intuitiveness which is surprising in terms of both the turn of events and their progress. By using a probabilistic description, forecasting and intuitive activities can be represented as in Figure 2.

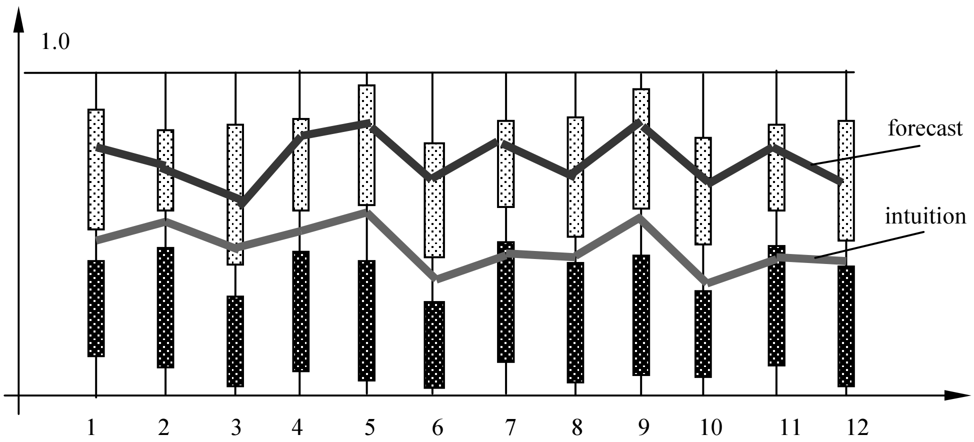

Fig. 2. Forecasting and intuitive predictions, where - the least probable events, - the most probable events

Each event is described by the set of parameters S(i) = {a(i,1),a(i,2),..., a(i,n)}, and the probability of its occurrence depends on time and is P(S(i),t) (Fig. 3).

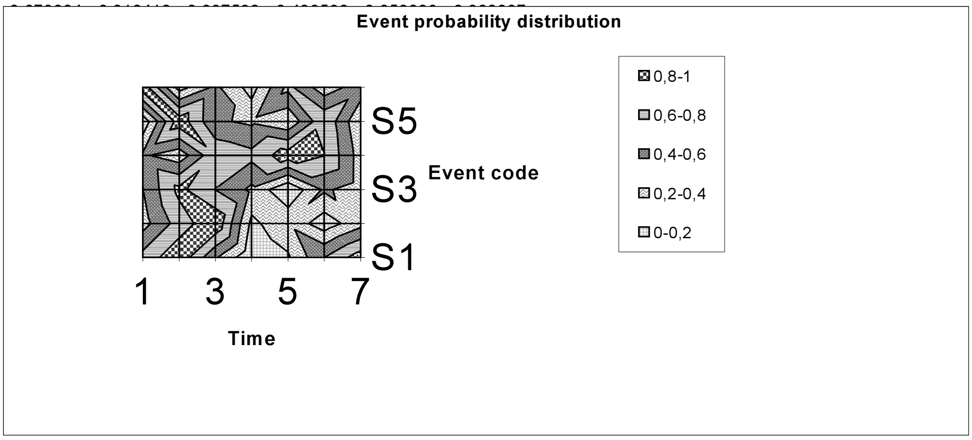

Fig. 3. Contour lines of the distribution of probability of events S as a function of time

1. Preparing the network for intuitive prediction

The next stage of preparing the neural network is the learning stage, for which we must choose those events that we feel intuitively rather than the most probable ones. The selection of these events will be made based on the empirical distribution (Fig. 4), which we create by using the contour lines in Figure 3 and considering the preferences of the intuitive zone by placing them in the centres of the normal distribution curves.

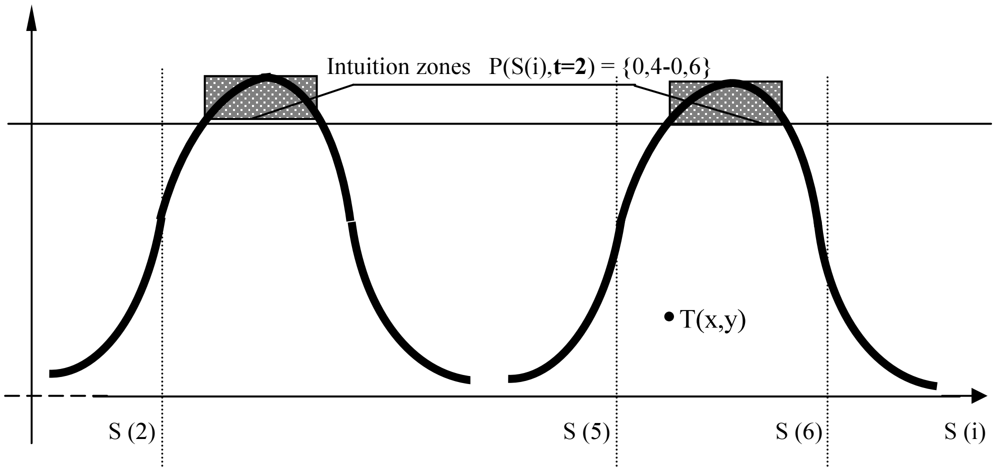

Fig. 4. Empirical event occurrence probability distribution modified for the preference of intuition zone interaction (0.4-0.6), for t = 2

This preparation of the empirical distribution will enable us to generate events (by the von Neumann method) which will be used in the neural network learning process. By choosing randomly point T(x,y), we verify the condition y<=g(x) that, in our case, is satisfied, which allows us to choose the event s(5) = round(x). As we have already stated, events are described by the set of output parameters that will be the result of processing the input parameters by the network. Parts of the input and output parameters may, of course, overlap, and the way of input data connection can be either parent (internal) or invasive (external) in character.

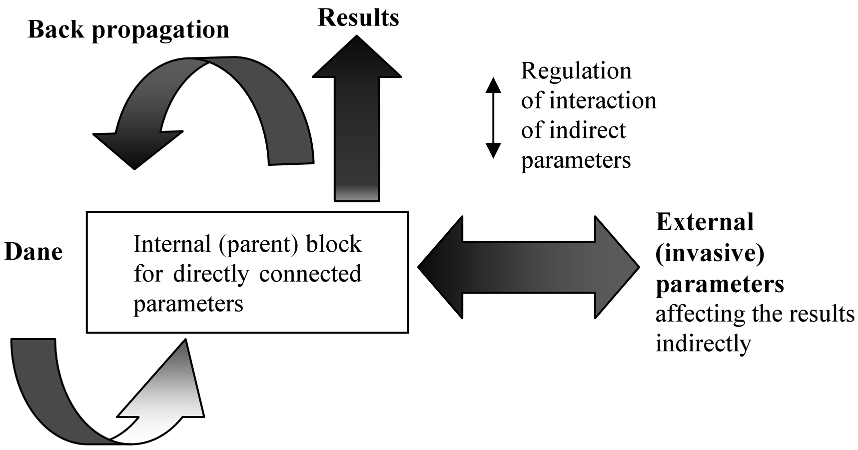

Fig. 5. The principle of interaction of the blocks (*planes*) of a neural network

2. Topology of connections and their matrix recording

The spatial network is composed of the *planes* of classical neural structures. In order to describe each of these planes, the number of layers and the number of neurons in each layer must be indicated. In the proposed arrangement of neural *planes* (Fig. 1) connections between the *planes* must be additionally recorded, which can be done by using the matrix of connections (Fig. 6). Inputs to, and outputs from the flat neural systems are also indicated in the figure.

$$MC = \begin{pmatrix} \{1,0,0\} & \{2,1,0\} & \{0,0,0\} & \{4,6,0\} & \{5,0,0\} & \{6,5,0\} \\ \{1,4,5\} & \{2,0,0\} & \{0,0,0\} & \{4,0,0\} & \{5,4,6\} & \{6,0,0\} \\ \{1,0,0\} & \{2,3,0\} & \{3,1,0\} & \{4,0,0\} & \{0,0,0\} & \{6,0,0\} \\ \{1,0,0\} & \{2,0,0\} & \{3,0,0\} & \{4,2,0\} & \{0,0,0\} & \{0,0,0\} \\ \{0,0,0\} & \{2,0,0\} & \{3,0,0\} & \{0,0,0\} & \{0,0,0\} & \{0,0,0\} \end{pmatrix}$$

Fig. 6. Matrix of connections recording the topology of the spatial neural structure shown in Fig. 7

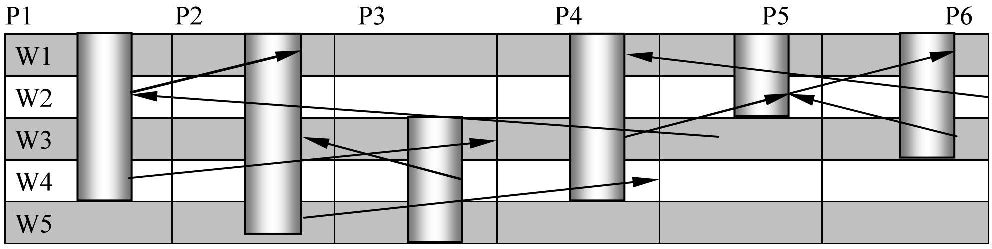

Fig. 7. Neural network structure built of 6 planes and interplanar connections indicated by arrows (Pi - i-th *plane*, Wj - j-th layer)

Prior to proceeding with recording connections, the *planes* should be arranged chronologically so that the transfer to the k-th layer of a given plane occurs always from the level of the (k-1)st layer of another *plane*. The matrix shown in Figure 6 has as many columns as the number of *planes* and as many layers as comprised by the global structure of chronologically ordered *planes*. The matrix is composed of sets, whose size is equal to the maximum number of connections of one of the layers of a particular plane.

3. Modification of the neural conversion algorithm for the spatial structure

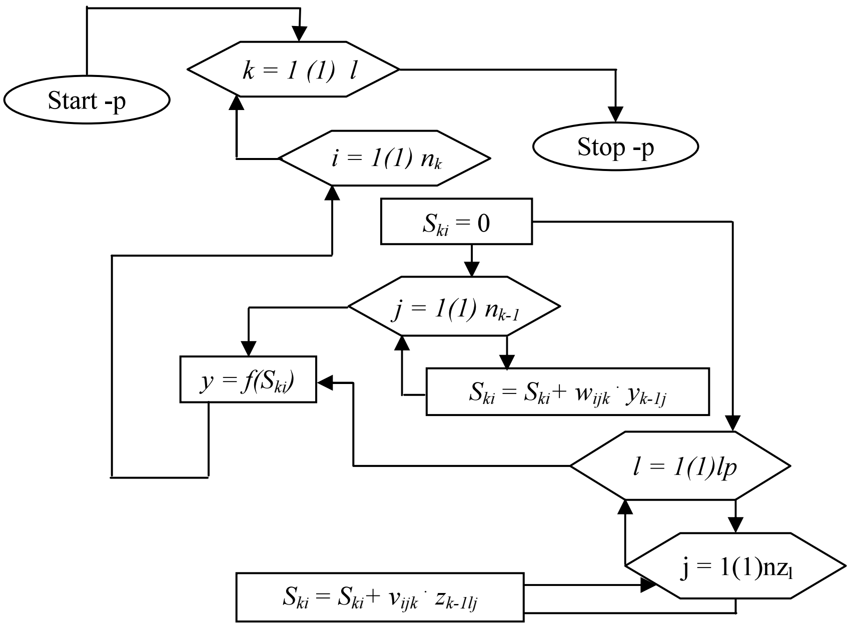

Fig. 8a. Algorithm of the interactions of internal (y) and external (z) parameters: k - layer number, i - number of a neuron in the k-th layer, j - number of a neuron in the k-1[st] layer; S_{ki} - sum of arguments in the i-th node; w, v - weights; l - number of the external module j - number of a connection

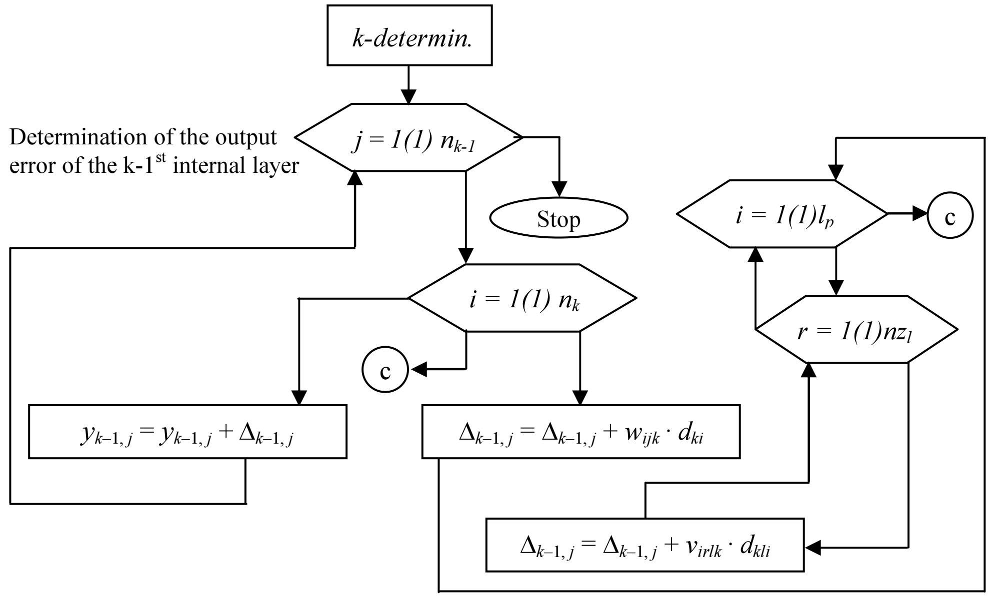

Fig. 8b. Simplified algorithm of partitioning the output error from the preceding k-1st internal layer

Figure 6a and b shows simplified variants of algorithms accounting for the interaction of external neural structures (planes). This interaction can be described in a greater detail by the following formulas:

$$y(i(l),l,r) = f(\sum_{i(l)=1}^{n(l)} w(i(l),i(l-1),l,r) * f(\sum_{p=1}^{lp} \sum_{i(l-1)=1}^{n(l-1,p)} w(i(l-1),i(l-2),(l-1),p) * \qquad (1)$$

$$* f(\sum_{i(l-2)=1}^{n(l-2,p)} w(i(l-2),i(l-3),(l-2),p) *$$

$$\bullet \quad \bullet \quad \bullet \quad \bullet \quad \bullet \quad \bullet \quad \bullet$$

$$* f(\sum_{i(0)=1}^{n(0,p)} w(i(1),i(0),1,p) * x(i(1),i(0),1,p)) ...)$$

where:

y(i(l),l,r) - signal at the output of the i(l)-th neuron of the l-th layer, r-th plane

w(i(l),i(l-1),l,p) - weight of the signal transferred from the i(l-1)-th neuron of the l-1st layer, p-th plane to the i(l)-th neuron, l-th layer, r-th plane

x(i(1),i(0),1,p) - signal at the i(1)st input of the1st layer, p-th plane

n(l,p) - number of neurons of the l-th layer, p-th plane.

The target function for, e.g., learning samples can be represented as follows:

$$F(W) = 1/2 \sum_{j=1}^{np} \sum_{p=1}^{lp} \sum_{i(p)=1}^{n(l(p),p)} (y_j(i(p),l(p),p)-d_j(i(p),l(p),p))^2 \tag{2}$$

where $d_j(i(p),l(p),p))$ - j-th learning sample at the i(p) output of the l(p)-th layer, p-th plane.

After differentiating relationship (2), we obtain gradient components in relation to the weights:

$$\partial F/\partial w(i(l),i(l-1),l,p) = \sum_{p=1}^{np} \sum_{i(p)=1}^{n(l(p),p)} (y(i(p),l(p),p)-d(i(p),l(p),p)) \prod_{s=l(p)(-1)}^{l} dv(i(s),p)/dv(i(s-1),p) \tag{3}$$

where: v(i(l),p) = function of conversion of the sum of the products of weights and signals at the output of the (l)-th neuron of the l-th layer, p-plane, d(v(i(0,p) = = w(i(1),i(0),1,p).
The gradient components are used for estimating the weight increment, Δw[ ].

Conclusions

1. Forecasting prediction which is based on the theory of probability does not always yield solutions positively verified by reality. Intuition is a phenomenon which is unexamined and not described by the mathematical apparatus. Many a time, intuition is supported by experience, which would encourage us to organize expert systems. Anyway, it appears fully justifiable to use neural structures, for example, with back propagation (or in other their variants and variety of learning and conversion).
2. When examining a spatial system, the intercorrelation effects between planes can be regulated by making their relative shifts. These shifts are chronological in character, as they actually mean a displacement in time.
   At the same time, they constitute additional parameters of learning optimization and modeling quality.
3. Describing situations through events and their parameters (Fig. 1) enables various real cases to be arranged, which creates an opportunity to move in a chosen sphere within the convention of the capability of intuitive predicting a situation.
4. A complex task is associated with the preparation of the learning set. This results not only from the multitude of parameters affecting the events, but also from difficulty in creating or recording a situation, in which intuition suggests an unexpected option that will subsequently appear to be positively verified (confirmed) by reality.

References

[1] Korbowicz J., Obuchowicz A., Uciński D., Sztuczne sieci neuronowe - podstawy i zastosowania, Akademicka Oficyna Wydawnicza PLJ, Warszawa 1994.

[2] Osowski S., Sieci neuronowe w ujęciu algorytmicznym, WNT, Warszawa 1996.

[3] Rutkowska D., Piliński M., Rutkowski L., Sieci neuronowe, algorytmy genetyczne i systemy rozmyte, WN PWN, Warszawa 1997.

[4] Rutkowska D., Inteligentne systemy obliczeniowe, Akademicka Oficyna Wydawnicza, Warszawa 1998.

[5] Tadeusiewicz R., Sieci neuronowe, Akademicka Oficyna Wydawnicza, Warszawa 1993.

[6] Koblitz N., Algebraiczne aspekty kryptografii, WNT, Warszawa 2000.

[7] Schneier B., Kryptografia dla praktyków, WILEY, WNT, Warszawa 2002.