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The Transistor Model of Neuron and Neuron Net*

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The article presents a mathematical description and the principle of the transistor neuron model as well as some simple examples of work of a net built of such models.

The neuron model built in the Independent Bionics Laboratory of the Institute of Automation of the Polish Academy of Sciences (Fig. 1) is a transistor device adaptable for work in a net with other models. In building the model, an attempt was made of using the basic known properties of the nerve cell including the property of facilitation of synapses and permanent memory of facilitation. A further attempt was made to preserve the temporary physiological scale by enlarging the voltage scale by a factor of 100. Moreover, independent regulation ranges, kept as large as possible, were used. The mathematical description [1] given below characterizes adequately the properties of the model. The resultant excitation voltage U_{e1} produced from one synapsis, which may be labelled 1 is related to the individual signals occurring in the past at the moments $t_{11}, \ldots, t_{1i}$ (Fig. 2). For the sake of simplicity time was indicated along the negative axis. For the moment $t_{10} = 0$, this relation may be expressed by the formula:

$$U_{e1}(0) = \eta_1 \sum_{i=0}^{\infty} \exp\left(-t_{1i}/T_1\right), \tag{1}$$

where η_i is coefficient taking into account the signal value and the weight of the synapsis, and T_1 is time constant for the synapsis, approximately the same for all synapses.

Since excitation derives from l synapses, the resultant excitation may be expressed by the summation:

$$U_e(0) = \sum_{k=1}^{l} \eta_k(w) \sum_{i=0}^{\infty} \exp\left(-t_{ki}/T_k\right), \tag{2}$$

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where $\eta_k(w)$ is coefficient of the k-th synapsis, which is usually a certain function (discussed below).

Condition for firing the neuron is the exceeding of the threshold value Θ by the excitating voltage U_e. It may be said that the relation of the frequency of generated pulses to the amount of excitation above the threshold is a logarithmic function (Fig.

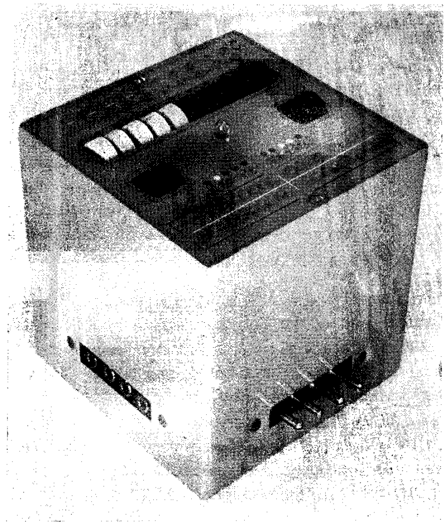

Fig. 1. Transistor model of neuron.

3). It is assumed that the pulses are identical and that their shape conveys any information. Then

$$
\begin{aligned}
&f_x(t + \lambda) = b \ln \left[U_e(t) - q\right] && \text{for} \quad U_e(t) - q > 1 , \\
&f_x(t + \lambda) = 0 && \text{for} \quad U_e(t) - q < 1 ,
\end{aligned}
\tag{3}
$$

where $q = \Theta - 1$, λ is delay between excitation and the generation of the pulse, and f_x is pulse frequency taken as the reciprocal of the time intervals between pulses.

As can be seen from equation (2), the resultant voltage of excitation is the result of the summation of the influence of the voltage on the various synapses at different times. This means that excitation of the neuron may be accomplished not only as the result of the appearance of an input signal which exceeds the threshold value, but may also appear in a series of subthreshold pulses the influences of which are summarized according to equation (2) (subthreshold, temporal, and spatical summation).

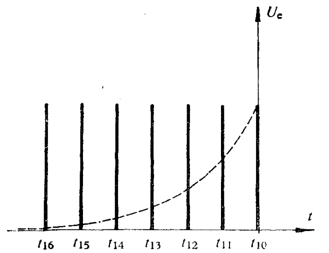

Fig. 2. The excitation voltage produced by individual signals occuring on one synapsis.

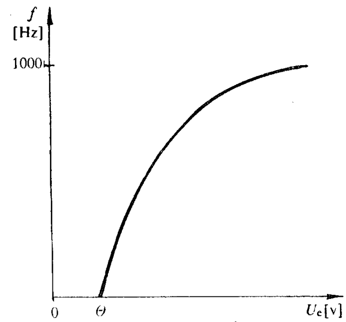

Fig. 3. Output pulse frequency-to-excitation relation.

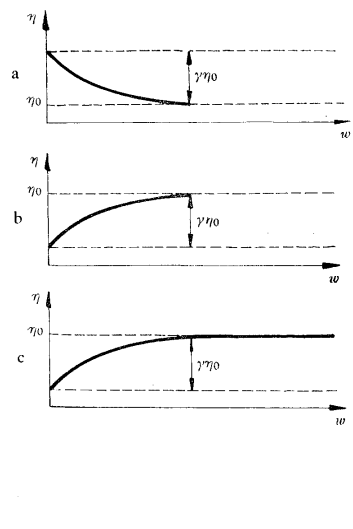

Fig. 4. Three possibilities of weight changes.

The mutual influence of particular synapses is defined by the weights $\eta(w)$, the values of which depend generally on past signals. There exist several possibilities for this dependence (Fig. 4):

a) The weight decreases with the number of input signals. Then blocking takes place which is a certain type of adaptation to the input signal. After cessation of the signal the weight returns to its initial value.
b) The weight increases to a certain asymptotic value and after cessation of the signal decreases to its initial value. This corresponds to the facilitation which must also be considered as certain type of adaptation.
c) The weight gradually increases to a certain value which is maintained even after cessation of the signal. This corresponds to the permanent memory of facilitation.

The above mentioned phenomena are of long-duration, of the order of seconds or minutes. The weight functions may be described by the formula:

$$\eta(w) = \eta_0[1 - \gamma \exp(-w/T_p)], \tag{4}$$

where η_0 is final value of the weight, and T_p is time constant of the process of facilitation and blocking.

The intensity of the process of facilitation and blocking is expressed by a coefficient which takes on the values

$$\begin{aligned} &\gamma > 0 \quad \text{for facilitation, and} \\ &\gamma < 0 \quad \text{for blocking.} \end{aligned} \tag{5}$$

The variable w is a generalized signal which can be expressed as follows:

$$w = \sum_{i=1}^{\infty} \exp(-t_{ki}/T_w), \tag{6}$$

where the time constant of "memory lapse" of facilitation or blocking T_w takes on the values: $T_w \approx T_p$ in the case of nonpermanent memory, and $T_w = \infty$ in the case of permanent memory. The foregoing instances of weight changes may occur for different synapses, depending on their functions in the neuron.

The model for which the block diagram is presented in Fig. 5 has inputs with regulated weights. As its input voltages pulses may be used which correspond in shape and duration to the mediator substance emission into synaptic gaps. Negative pulses have excitating activity, while positive pulses have inhibiting activity. The summation block and filter transform the input voltages into voltages corresponding to each other in postsynaptic potential.

Capacity and resistance of the filter correspond to a certain substitute capacity and resistance of the postsynaptic membrane. Due to this filter and to the RC output circuit of the previous neuron, so-called temporary summation and synaptic delay come into play. The next two blocks

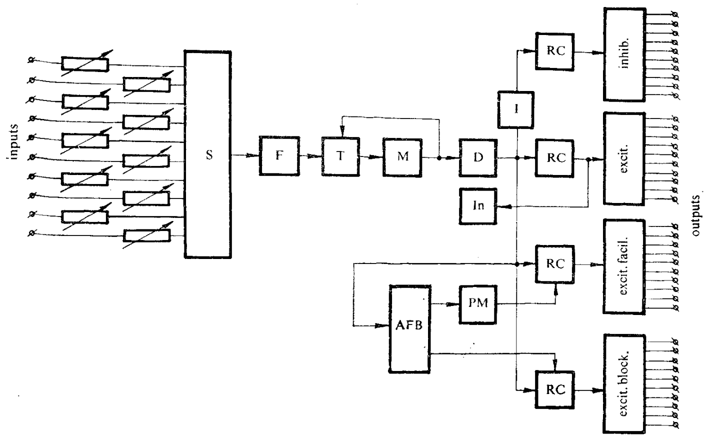

Fig. 5. Block diagram of the neuron model (S — summation, F — filter, T — treshold, M — multivibrator, D — axon delay, I — invertor, RC — time constant, In — light indicator, AFB — facilitation and blocking amplifier, PM — permanent memory).

constitute the threshold multivibrator which generates pulses only when the resultant excitation exceeds the given threshold value. The frequency of the generated pulses is connected with the amount of superthreshold excitation by an approximate logarithmic relation. Such transfer characteristic was obtained with the help of a certain circuit. This circuit brings about the proper change in the threshold as a function of time after the generation of each pulse by the multivibrator. This change is a sudden growth of the threshold after discharge and then falling back to the initial value (relative refraction). Pulses from the multivibrator have a rectangular shape and correspond to the action potentials in the nerve cell. Of course, their shape differs from the shape of physiological action potentials. However, since these phenomena, connected with the shape, e.g. refraction, were modelled in a different way, a true reproduction of this shape seemed inappropriate.

The next block is the system simulating the axon delay which can be connected from the outside. This delay can be regulated throughout a range from 1 msec to 10 msec. The next part of the system is a model of the synapsis. The pulses charge a capacitor (block RC), having a discharge time constant of 4 msec, with a very small time constant. The changes of voltage on the capacitor correspond to the emission of the mediator. These pulses appear in the model's outputs. The signals in the excitation outputs have negative values. The inhibiton pulses in the inhibiting outputs are obtained analogously after inversion of the impulses from the multivibrators.

The model has two additional outputs: an excitation output with facilitation and an excitation output with blocking. These circuits are analogous to the output circuits described above with the difference that their transfer functions are controlled by the facilitation and blocking amplifier (AFB). At the initial moment, the pulses cannot appear in the excitation outputs with facilitation and in the excitation outputs with blocking, however, they appear with full amplitude. At the same time, the capacitor in the amplifier input charges with pulses from the multivibrator, and due to this, the excitation output with facilitation controlled by the amplifier gradually becomes unstopped, and the amplitude of output pulses grows from zero to maximum. Analogously the excitation output with blocking becomes stopped. The time constants of facilitation and blocking de-

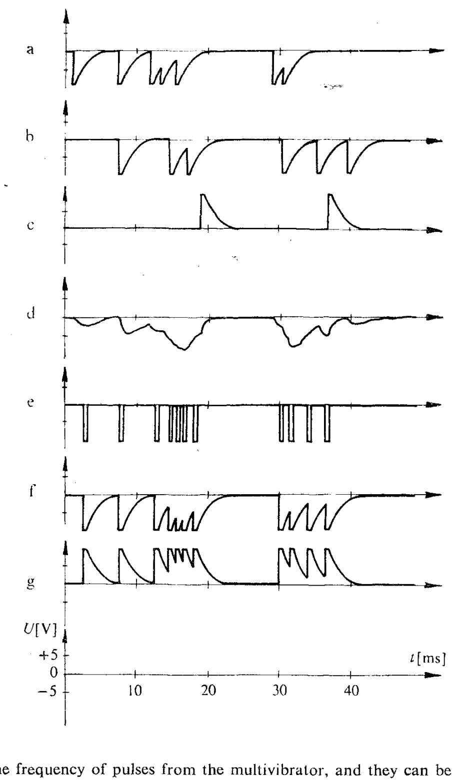

Fig. 6. Waveforms of some voltages in the model (a, b, c — inputs' waveforms; d — filter's waveform; e — multivibrator waveforms; f — excitation input's waveform; g — inhibition input's waveform).

pend, among other things, on the frequency of pulses from the multivibrator, and they can be regulated in anrange from several seconds to 2 minutes by gain of the amplifier. The output with facilitation was additionally supplied with permanent memory, that is to say, an output once facilitated remains facilitated (if necessary) as long as desired regardless of whether the neuron gives pulses or not. There exists the possibility of taking advantage of permanent memory also by engagint it only when the logical product of the proper voltage from the amplifier and the external general excitation is fulfilled on its input. The above properties have an actual meaning in connecting and exploring neuronal nets.

The model is equipped with a light indicator by which the state of the model can be appraised. The first experiments showed that without light indicators observation and drawing conclusions from the operation of the nets would be very difficult.

The following technical data relate to the neuron model discussed here:

1. 10 inputs of regulated weight ranging from 20 kΩ to 500 kΩ;
2. threshold regulated between 0·3 V – 6 V (with relation to the signal given for one input with the maximum weight);
3. pulse width from the multivibrator 0·5 msec, amplitude 12 V;
4. absolute refraction 0.7 msec, a relative refraction approx. 100 msec;
5. frequency range 0 to 1000 Hz;
6. time constant for the filter 4 mscec;
7. time constant for decay of the output potential simulating the mediator 4 msec;
8. maximum value of the direct current component of the potential simulating the mediator 8 V;
9. time constant of facilitation and blocking ranging from several seconds to 2 minutes;
10. 10 excitation outputs, 10 inhibitation outputs, 10 excitation outputs with facilitation and 10 excitation outputs with blocking.

Fig. 6 shows the wase forms of selected voltages in the model. A net which can be connected in any manner desired was created from 40 such models. The first investigations were completed on simple structures consisting of several models and likewise on more complicated structures researching, e.g. phenomena of synchronization in the peripheral nervous system, controlling the muscles, and some problems connected with perception.

By way of example a simplified model of the acquirement of a conditioned reflex and its extiction is shown in Fig. 7. Fig. 8 represents a system which simulates the problem connected with perception. The net shown in the Figure can be used to

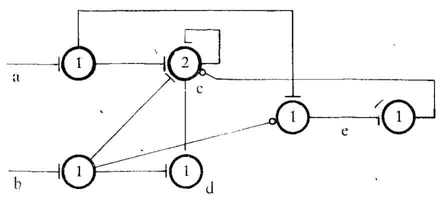

Fig. 7. The simplified model of conditional reflex (a — conditional stimulus; b — unconditional stimulus; c — association; d — indicator; e — extinguishing loop; ⊣ — excitation; ⌐ — excitation with facilitation; —o inhibition). (Both inputs into d are ⊣.)

differentiate contours and corners by utilizing the rule of lateral inhibition. The base of the net which was built was a complicated and expensive model, but it has many properties and wide ranges of regulation. However, after obtaining reliable data about the operation of a net built, as in our case, of 40 elements and about the factors

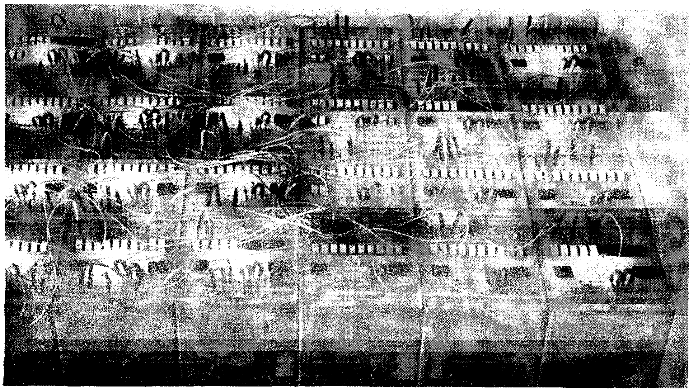

Fig. 8. One model of neuron net.

determining its properties, more simple, significantly smaller elements having more limited ranges of regulations and which, of course, are much less expensive, could be advantageously considered.

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Tranzistorový model neuronu a neuronové sítě

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Článek obsahuje matematický popis tranzistorového modelu neuronu, jeho principiální zapojení a několik příkladů sítí sestavených z popisovaných modelů.

Model napodobuje základní vlastnosti nervové buňky. Model je vybaven 10 vstupy s nastavitelnými vahami a má čtyři druhy výstupů typu inhibice, excitace, excitace s facilitací a excitace s blokováním. Adaptivní vlastnosti modelu, jako je facilitace a blokování výstupů a stálá paměť, umožňují provádět velmi zajímavé pokusy se sítěmi složenými z těchto modelů.

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