
**ACOUSTICS OF LIVING SYSTEMS:
BIOLOGICAL ACOUSTICS**

Model of a Neuron Trained to Extract Periodicity

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Abstract—In the auditory system, there should be elements that convert temporal parameters into spatial ones. To simulate such conversion, various neural networks are used. In this study, we modeled this conversion, carried out by one complex neuron on the basis of learning without a teacher. We postulate that conversion of the time code into a spatial code is observed at the input of the model. We admit that every aciculum of a complex neuron responds as a coincidence detector, and after each coincidence at any synapse, the neuron generates a spike. Every spike at the output of a neuron changes the weight of all acicula according to the Hebb principle. Training of the model is done without a teacher simply owing to model's multiple perception of a certain type of signals. In the given case, such signals are the actual activity of the cochlear nucleus of frog, which arises as a response to an amplitude-modulated tone. After the action of such signals, the model behaved as a detector of the modulation frequency used during training. Such a situation existed up to modulation frequencies near 40 Hz. At higher modulation frequencies, the model even extracted signals with a doubled modulation period.

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INTRODUCTION

Sound signals transmit information about the object emitting them in frequency-temporal form. Analysis of frequency changes is conducted at the periphery of sound using various specialized structures, including the cochlea of mammals. Temporal information is extracted and analyzed exclusively in neural networks of an auditory analyzer. The decisive role of precisely temporal analysis is demonstrated, for instance, by the fact that a person can perceive whispered speech in which the spectral characters are reduced to a minimum, speech artificially produced only through three filters [1], and even speech produced through single-channel electronic cochlear prostheses [2]. A decrease in the number of peripheral filters from several thousand (typical for normal hearing) to eight (after electronic cochlear prosthetics) detracts hardly at all from the intelligibility of speech in standard tests [3]. Certain data on the monitoring of human brain activity also testifies to the determining role of precisely temporal changes in the envelope [4].

Study of the activity of single fibers of the auditory nerve has shown that at this level of the auditory path, temporal changes in the signal envelope are coded exclusively by temporal distribution of neuron impulses, the activity of which continues the entire time of the stimulus [5–7]. The effectiveness of this coding is not very high, so even in the optimal range of stimulus intensities (where the impulse frequency depends the most strongly on the level), modulation of the impulse density of a fiber is usually less than the modulation depth of the signal itself. In neurons of the

cochlear nucleus, there is an increase in the effectiveness of temporal coding of changes in the envelope [8, 9]. As well, the dependency of the main impulse density on the modulation frequency for the majority of cells remains quite weak [10]. However, this property is not related to the so-called phasic cells responding to an unmodulated signal by initial discharge alone. In such neurons at a large modulation depth of the signal, pulsed discharges (spikes) arise as a response to each modulation, which leads to a linear dependence of the impulse density on the modulation frequency. Such correspondence is observed until a certain limit frequency, and after it is exceeded, the response returns to the initial type and spikes arise only at the onset of the signal [7].

The coding mechanism of the temporal parameters of the signal changes quite sharply in the next large center of the auditory path: the colliculi of the mid-brain [11–14]. At this level, there is a decrease in the highest frequency of changes in amplitude produced by single neurons. On the other hand, enhancement of the degree of response synchronization occurs with signals having a comparatively low frequency and small modulation depth [13–15]. In addition, at the level of the colliculi, cells begin to be encountered that are tuned to the optimal frequency of changes in signal amplitude. An even larger number of similar cells were discovered in the most central divisions of the auditory analyzer and primarily in the auditory core [16]. Note that according to some data, neurons reproducing the periodicity of the signal by the periodicity of impulse and neurons with maximum impulse density at a cer-

tain modulation frequency can be found in the auditory center, but in different divisions of it [17].

We imagine that coding from temporal to spatial is a necessary stage of processing sensory information. Therefore, in a number of laboratories, models of the processes leading to such conversion have been developed. Nearly all such models are based on deterministic schemes. Meanwhile, there are grounds to assume that neurons/detectors of a certain periodicity do not arise in the brain as a consequence of rigid genetically determined mechanisms, but are generated in the process of learning and training. An especially large amount of data have appeared in recent years testifying to the high plasticity of sensory analysis mechanisms [18–20].

From psychosomatic studies, it is well known that precisely problems requiring temporal analysis are especially sensitive to the training of those being tested. The thresholds of amplitude modulation [21] over the thresholds of determining the duration [22] can be enhanced after training by almost an order. This contrasts sharply, for instance, with the absolute threshold of hearing, the determination of which hardly requires any training. Especially convincing in this regard were the experiments by Tumarkina and Dubrovskii [21], since they showed that training lowers the threshold for discovering amplitude modulation only at low modulation frequencies, where it is impossible to use spectral characters. In a recent study by American authors [23], these data were confirmed, and it was shown that in parallel to a decrease in thresholds, amplification was observed in cortical responses to stimuli included in the training process.

The electrophysiological data testify to the role of training, especially the numerous data on songbirds and owls. Here it is necessary to carry out behavioral experiments testifying, for example, to communication of signals emitted by a specific population animals and characteristics of the auditory system of this population. From the large quantity of literature related to training of birds, we point to a study in which it is shown that for correct reproduction of parental song, a baby nightingale should listen to it no less than 15–20 times [24].

Naturally, there exists a set of models that reproduces to a particular extent real nervous structures and is capable of training. However, there are relatively few models of neural networks or single neurons trained based on real impulses of neurons of the auditory system detected in experiment. We can only point out study [25], in which to classify the real neural activity caused in cells of the auditory path by signals arriving from different directions, standard neural networks trained by back propagation of error were used. In another small work, the neural network was used to analyze impulse periodicity caused by tonal segments [26].

In our previous works, we also tried to simulate the formation of neurons/periodicity detectors using the information contained in the temporal pattern of an impulse. In all these works [27–29], training was carried out with a “teacher” that informed the system to which class a particular training sequence signal belongs. In application to real neural structures, we assumed that such a teacher can be, for example, a signal from the higher divisions of the auditory path.

Simple two-layer and three-layer neural networks were used. Input signals were the impulses detected from real neurons of the cochlear nucleus of frog under the action of amplitude-modulated tones. Results have shown that the two-layer network with training by back propagation of error results in extraction of periodicity of the amplitude-modulated signal, but only under the condition that the initial modulation phase is known [27].

Actually, these neural networks extract not so much the periodicity per se, but the time pattern of the response caused by the stimulus. As for attempts by the three-layer model to carry out extraction of signal periodicity with any initial modulation phase [28], experiments have shown the sufficiently limited possibilities of such an approach. However, electrophysiological results obtained in recent years clearly show that trained structures can be not only neural networks, but also individual nerve cells.

Development of experimental techniques makes it possible to track the functioning not only of an individual neuron, but also its individual elements: dendrites and even synapses. These studies have indisputably shown that the majority of synapses, in any case, those which correspond to neuron-acceptor acicula, possess sharply nonlinear properties and the output signal can be determined by the temporal pattern of previous inputs [30,31].

In our suggested model, it is supposed that individual acicula exhibit sharp amplification of the output signal at a certain value of the time interval between input spikes. Actually, we postulate that acicular neuron inputs function as coincidence detectors [31].

Another research direction in recent years is already connected to training questions at the level of single neurons. It is known that areas of the cortex responsible for perception of frequently produced signals become more extensive and react to a signal more effectively. We refer, for example, to [32], in which it is shown that tonotopical organization of the auditory cortex is in many respects determined by previous auditory experience.

As well, practically all modeling works connected with training of neurons use the well-known Hebb principle [33], which in the original publication reads: “When an axon of cell A constantly provokes a response from cell B, in one or both cells, there occurs the mechanism of growth of metabolic changes either

leading to an increase in the efficiency of A or to simplified generation of a spike in B.”

Numerous subsequent studies [34, 35] have confirmed the interdependence of the efficiency of individual neuron inputs with the output activity of a cell. In addition, these studies have made it possible to specify and expand the formulation of the principle, having included in it the position about the decreased efficiency of synapses where the mentioned conformity between an input and the impulse response of a cell is absent. Note that in rare instances, anti-Hebb training has been observed, leading to depression of inputs causing impulses at the output of a cell [36].

In the present work, we tried to simulate conversion of the time code of periodicity into a spatial one using a single-neuron model. Such a neuron has a dendrite network with acicula, each of which is a coincidence detector.

Acicula are flexible: their weight increases during cell response caused by input to this aciculum. As well as in [27–29], we do not try to model peripheral links of the auditory analyzer; we directly subject the model to impulse activity detected experimentally in the auditory nuclei of frog under the action of amplitude-modulated tones.

TECHNIQUE

Detection of Electrophysiological Data

Electrophysiological experiments were carried out on grass frog (*Rana temporaria*) immobilized by allopurinol. The basic methodical approaches used in detecting impulse activity were described in detail earlier. All operations were carried out according to rules of dealing with experimental animals, and the operation was performed under conditions of cold [37] and local anaesthesia. Detection itself was carried out in conditions of immobilization and dermal respiration. Activity was detected by liquid microelectrodes about a micrometer in diameter from single neurons from dorsal nuclei of the medulla oblongata (a homolog of the cochlear nucleus of mammals). A step motor submerged the electrode vertically downwards through a vascular strip. After revealing the activity of a single cell, its characteristic frequency and the threshold at this frequency were determined. Further, the signals were tone segments of the characteristic frequency amplitude-modulated by a sinusoidal signal. The duration of segments, as a rule, was 0.3 s, and the tracking period, 0.4 s. The sound level measured near the eardrum by a calibrated nozzle microphone was 70–90 dB USD (ultrasonic diagnostics) and was chosen at 20–30 dB higher than the threshold of cell reaction. Sinusoidal modulation frequencies of 5, 10, 15, 20, 25, 30, 40, 50, 60, 70, 80, 90, and 100 Hz were used at modulation depths of 50–100%.

Detected bioelectric activity, in which spikes of an investigated neuron exceeded the noise background by

several times, hit the Schmidt trigger and was converted to a sequence of standard impulses with a duration 0.5 ms, the moments of occurrence of which corresponded to the moments at which spikes occurred. This information was carried through an analog-to-digital converter into the memory of a computer and was saved as a file containing values of consecutive interspike intervals. This file was also the input of the neural model. In addition, during biological activity detection, the poststimulus histograms of reaction to each segment and histograms of the distribution of probability that an impulse occurred in the period of modulation [38] were constructed.

Description of the Model

The main variant of the neuron model included 200 inputs (acicula) with a randomly chosen initial force of synaptic bond from 0 to 1 (by weight) (Fig. 1). All acicula reacted instantaneously to the arriving (firing) signal, after which each of them changed its internal state in such a way that the optimal reaction to a repeat signal corresponded to the characteristic, for the given aciculum, delay of its arrival. The optimal delay values from the first aciculum to the last change linearly with a step of (Δt) 0.5 ms from a value of 0.5 ms to a value of 100 ms. The arrival of each new input discards its time count for the given aciculum. Note that in such a variant of the model, at the input of a neuron, two acicula cannot simultaneously react with the optimal delay; the synaptic response hitting the trigger area of the neuron after summation of inputs is sufficient to generate a spike.

The training process consists in a change in the weight of acicula in accordance with the simplified Hebb rule. As well, the weight of the aciculum to which a signal arrives with the optimal delay, i.e., of the aciculum that actually causes the spike at the output of the model, somewhat increases and the weight of all other acicula decrease. Figure 1 illustrates the behavior of the model as two impulses arrive at the input with an interpulse interval of $n\Delta t$ ms. Note that during intervals between impulses exceeding 100 ms ($200\Delta t$), impulses are not generated and the weights remain unchanged.

Several algorithms of the model were used. In several cases, the initial weights of all acicula were fixed at 0.5. Several varying algorithms for changes in weight were used. In one of them (the linear variant), the increase in the weight of the aciculum causing the cell response corresponded to 10% and the decrease in the weight of all remaining acicula was almost 0.5% (Fig. 1). In such a variant of the model, the weight of some inputs after training were able to exceed unity. In other variants of the model under the same system of changes in weight, the hyperbolic tangent of the obtained weight value was used as the resulting parameter. As well, naturally, the weight never attained unity, but the quantity of the increment was not constant and

decreased for synapses that already achieved significant force. Thus, subsequent increments were less significant than the initial ones. We again emphasize that it was not our goal to make a detailed comparison of the results obtained in different modifications of the model and we can say that fundamental distinctions between them have not been noted, since the model itself is purely qualitative. We will show the main data for the variant with a random value of initial weights and linear change in weight after generation of an output impulse. The model was implemented using Matlab 7.

RESULTS

Figure 2 shows the resulting weights of 200 inputs obtained after signals were produced at the input of a model having a random initial distribution of weights generated by neurons of the auditory nucleus of the medulla oblongata of frog under the action of amplitude-modulated tonal signals with fixed modulation-frequency values. In this specific variant of the experiment, for each frequency of the impulse of a training signal, we used all experimental data available at our disposal. Naturally, at different modulation frequencies, both the number of real neurons used in training and the total number of training impulses varied. The weights of synapses changed according to the first of the variants, so they could reach values larger than unity.

From the data shown in the figure, it is obvious that training sharply changed the distribution of the model's synaptic weights. At rather low modulation frequencies of training sequences, usually two basic maxima were revealed. One of them corresponded to the period of the signal envelope used for training, and the other arose at small periods, apparently owing to the existence of bursts of impulses generated in response to one period of the envelope. In our data, the brightest extraction of the modulation period used in the training sample was at 25 Hz. The weights of synapses having characteristic delays of around 40 ms after training were substantially higher than any others (Fig. 2b).

Note that modulations in the range of 20–30 Hz are actually present in the most typical communication signal of the investigated type generated by males during the courting period [39]. The insignificant additional maximum arising after training by sequences of impulses generated by neurons of the cochlear nucleus under the action of a signal with a modulation frequency of 25 Hz corresponded to a doubled value of the modulation period (80 ms).

With increasing modulation frequency of acoustic signals used to create the training sequence, both the relative amplitude and the number of maxima with multiple values of the modulation period increased. Note, however, that we never observed selective ampli-

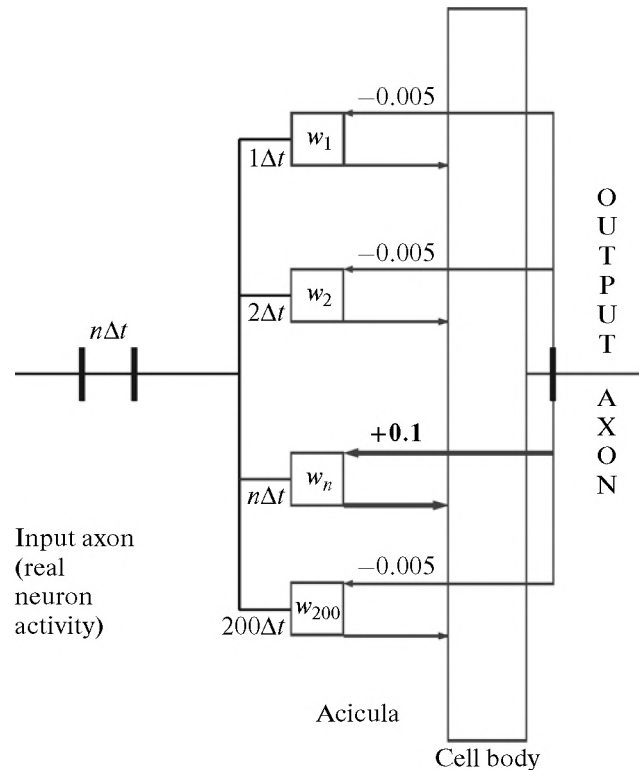


Fig. 1. Block diagram of model of self-training neuron with input elements of acicula tuned to specific delay between input impulses of threshold scheme in cell body and system for regulating weight of synapses according to the Hebb principle. The diagram illustrates the case when a pair of impulses with an interval of $n\Delta t$ arrive at the input of the neuron.

fication of the weights of inputs corresponding to a doubled modulation frequency (i.e., to a twice-reduced period).

Figure 3 shows the resulting data on the character of the output reaction of the neuron model to signals arriving from all studied cells under the action of signals of various frequencies after training. In the course of model training, we obtained signals in accordance with modulation frequencies of 25 Hz (Fig. 3a), 40 Hz (Fig. 3b), and 80 Hz (Fig. 3c). It is well seen that at a training frequency of 25 Hz, the generated model neuron appeared to be a rather accurate detector of the corresponding modulation frequency.

Models “trained” at frequencies of 40 and 80 Hz also extract the frequency used for training; however, the efficiency of its extraction is not so high. We connect this with the fact that after training at these frequencies, there was an increase in the weights corresponding to the others, primarily to small intervals between impulses. In addition, in Fig. 3c, the maximum corresponding to the frequency shifted an octave downwards is clearly distinguished. This maximum arose due to the frequent presence in training sequences of doubled intervals corresponding to half

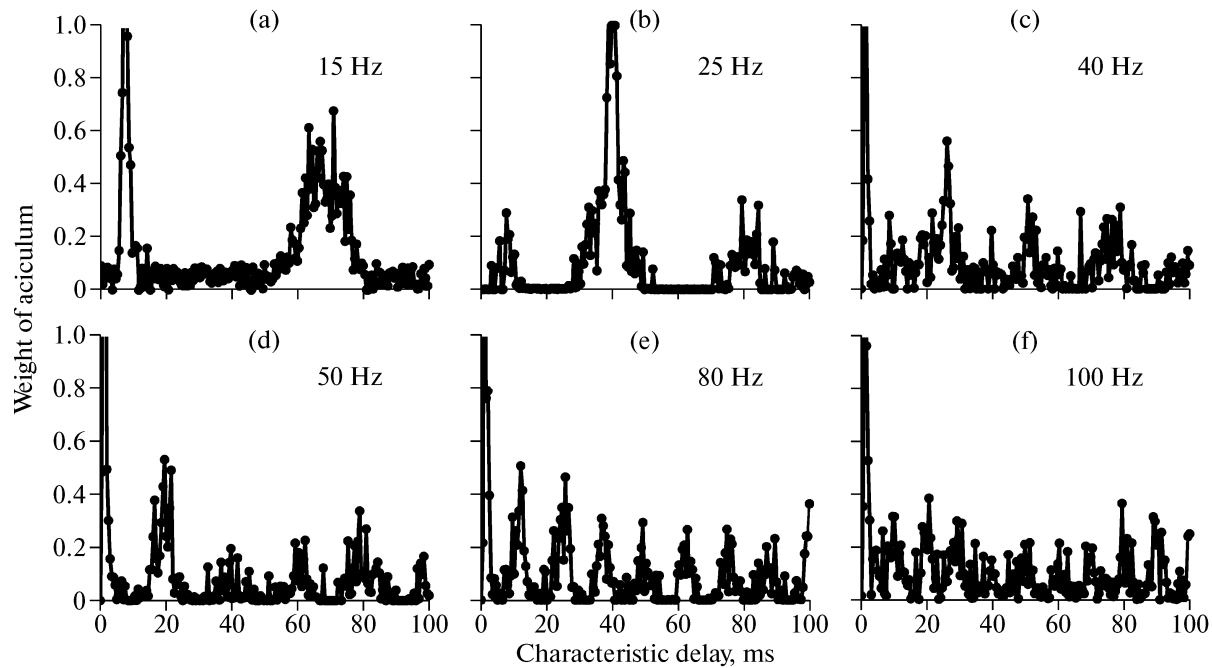


Fig. 2. Resulting weights of 200 inputs of the model after production of sequential pulse activity to the input, detected in all studied neurons of the dorsal nucleus of frog under the action of amplitude-modulated tonal signals. Random distribution of initial weights and linear algorithm for the change in the weight of bonds. (a) Modulation frequency (MF) 15 Hz, number of neurons used in training (NN), 11. (b) MF, 25 Hz; NN, 6. (c) MF, 40 Hz; NN, 14. (d) MF, 50 Hz; NN, 10. (e) MF, 80 Hz; NN, 8. (f) MF, 100 Hz; NN, 5.

the modulation frequency. Note that precisely such octave errors are characteristic in psychosomatic studies.

As we have repeatedly noted in physiological studies [40–42], neurons of the cochlear nucleus of a frog strongly differed among themselves in the efficiency of extracting the periodicity of the sound signal envelope.

It is natural therefore to assume that the role of different neurons, the impulses of which were included into the training sequence, may have been various. If the input impulse was chaotic, it did not lead to the targeted change in the input weights. At the same time, accurate periodicity of an input impulse should promote the detector properties of an output neuron.

We consider this question in more detail with the example extracting a modulation frequency of 20 Hz. Figure 4 shows the resulting values of weights obtained after training the models by inputs corresponding to a impulse of specific individual neurons of the cochlear nucleus of the investigated object. The results shown in the top row correspond to the data obtained as weights changed according to a linear law and at random initial values of the weight values of synapses. The data in the bottom row were obtained in conditions when the initial values of all weights were 0.5, and the final values were transformed by the function of the hyperbolic tangent.

Figure 4a shows the results after training by signals generated by cell 1 for which not very accurate repro-

duction of the modulation frequency was observed and the frequency of impulse tracking was low. Under chaotic distribution of the initial weights (top row), the weights of synapses obtained after training also were completely chaotic. It is interesting that when the initial weights are equal, the picture appears somewhat different. Though the majority of weights remained invariable (nearly 0.5), nevertheless, an insignificant maximum of weights in the range of 50-ms delays were distinguished. Note that the number of training sequences in this case was probably insufficient to develop accurate detector properties. Figures 4b and 4c show the results after training by a impulse from neurons (cells 2 and 3) that well reproduced a modulation frequency of 20 Hz. In this case, nonuniformity of the weight distribution and a quite accurate maximum around 50 ms are quite obvious.

Thus, in our rough assumptions of the model's structure, even training by signals arriving from one real neuron is quite sufficient for fast generation of a detector of a fixed modulation frequency.

DISCUSSION

We consider currently existing models for extracting periodicity. In some of these studies, it was not the goal to create neurons/periodicity detectors; they simply estimated the variations between impulse fluxes in

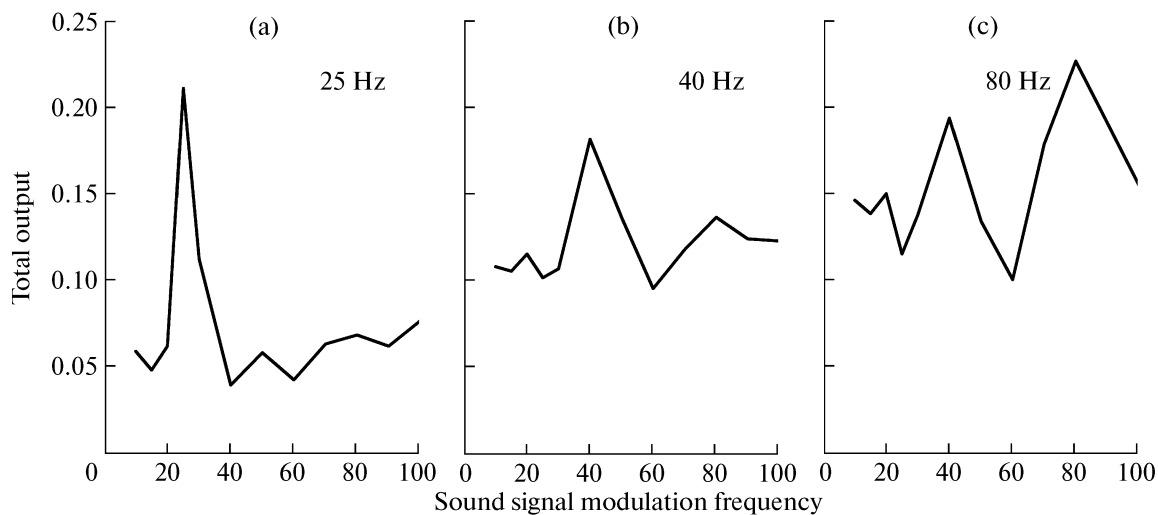


Fig. 3. Normalized total output (synaptic potential) for three variants of the model trained under the action of signals with modulation frequencies of (a) 25, (b) 40, and (c) 80 Hz, respectively. In the training process all reactions from all studied neurons to corresponding modulation frequencies were used.

cells caused by signals with various modulation frequencies.

So, in [43], the modulation frequency of a signal was classified, proceeding from an analysis of impulse activity of neurons of the auditory system of a cricket. The modulation depth was 100%, and the subsequent modulation frequencies differed by a factor of 2; i.e., the problem was rather simple. It was solved by integration of neuron activity with different time constants. With an optimum choice of time constants, such classification at low frequencies (in hertz) was quite effective, and in the auditory nerve, it was retained to modulation frequencies exceeding 100 Hz.

The majority of models for converting the time code of periodicity into spatial, having neurophysiological bases, are constructed on the reproduction of responses of so-called cells with alternating discharge, which are quite numerous in the ventral cochlear nuclei of mammals.

Such cells indeed generate the maximum number of impulses under the action of signals with a specific modulation frequency; however, this only occurs due to the negative feedback arising after each spike generated by a neuron [44–49]. The fact that precisely the postspike decrease in excitability (generalized adia-phoria) determines the features of the behavior of these cells, has been demonstrated on neurons of the dorsal cochlear nucleus of cat [50] via determination of the functions of the expected impulse density [51].

The duration of generalized adia-phoria of the period actually determines the value of the modulation frequency at which the activity maximum in models of this kind is observed. The approach based on the creation of neurons/detectors to account for adia-phoric properties of single neurons encounters a number of substantial difficulties. The most obvious of them

reduces to the necessity that there exist a population of neurons with varying, by at least an order of magnitude, values of absolute adia-phoria.

If in similar models absolute adia-phoria is replaced by relative adia-phoria, the optimum modulation frequency should change with change in signal level. In addition, it is known that neurons of this kind do not reproduce the envelope with decreasing modulation depth [15].

The assumption on the existence of real internal oscillatory mechanisms in cells with an alternating type of discharge, elaborated by a group of researchers from Darmshtadt University [52], has to date not been physiologically substantiated to a sufficiently convincing degree. [53].

Another class of models for converting time code to spatial code is presented in [54]. The authors assume that tuning to a certain modulation frequency is carried out in neurons of the cochlear nucleus and in cullicoli neurons owing to the interaction of a weak, long, undelayed exciting input and a stronger, but shorter and delayed deceleration. Varying the delay times and amplitude of corresponding inputs, it is quite easy to obtain transmission characteristics on modulation with a well expressed maximum. One more recent study [55] serves as a development of this model with the inclusion of different types of neural elements of the auditory path and allowance for not only delayed, but also lateral deceleration.

In essence, all similar models represent schemes of coincidence necessary for use of correlation methods to extract periodicity. The first such model was suggested in the mid-20th century [56]. Mathematical consideration of correlation models of periodicity based on neurophysiological data has been carried out recently in [57]. It is shown that these models can be

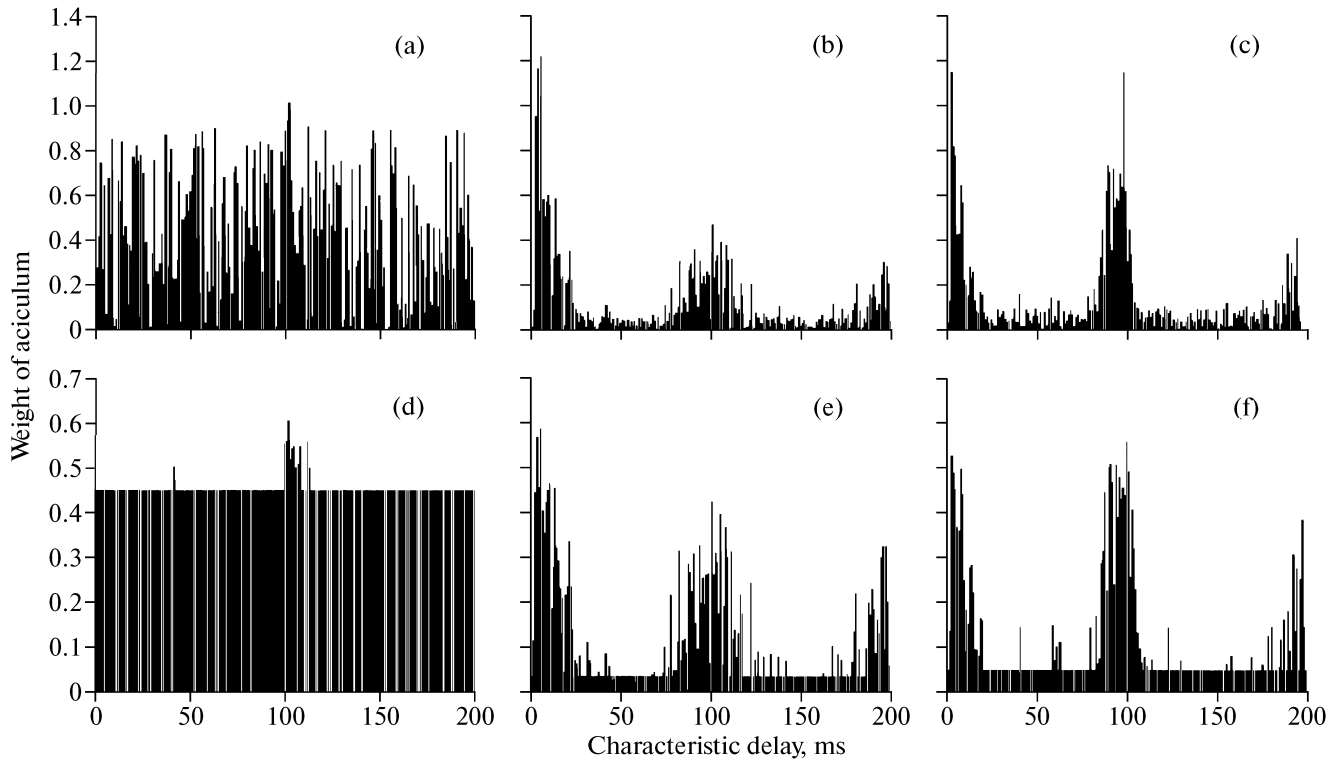


Fig. 4. Resulting weights of 200 inputs of the model after production of sequential impulse activity to the input, detected in individual neurons of the dorsal nucleus of frog under the action of amplitude-modulated tonal signals with a modulation frequency of 20 Hz. (a) Neuron 1, number of productions 46; (b) neuron 2, number of productions 12314; (c) number of productions 2201. The top row corresponds to random distribution of initial weights and linear algorithm of changes in the weight of bonds; the bottom row corresponds to uniform distribution with a weight of 0.5 and conversion using the hyperbolic tangent.

divided into two classes by the type of formation of elements of the delay line. In some of the models, recurrent excitation of a nerve cell by positive feedback with a fixed delay is supposed [58]. In other models, it is supposed that as sound acts on the input of a neuron, two signals arrive at a cell, one of which has a fixed delay. In [59], coincidence detectors have been implemented owing to delayed facilitation of an input such as is approximately implemented in the acicula of our model.

There is another group of models in which extraction of periodicity is not linked to any specific neurophysiological data and the goal of simulation is more or less successful reproduction of psychoacoustic results. In an overwhelming majority of cases, they also use the correlation approach [60, 61]. Autocorrelation models for extraction of periodicity encounter a number of difficulties. However, the main one, in our opinion, remains full neglect of the role of prior experience in the creation of neurons/periodicity detectors.

Note that in many cases, for certain kinds of animals, periodicity of emitted signals agrees well with the optimum frequencies of amplitude modulation of neurons of various structures of the auditory path. Moreover, in different populations of one kind of ani-

mal (for example, geographically isolated), a positive correlation has been revealed between characteristics by frequency shifts in periodicity of an emitted signal and optimum values of perceived periodicity [62]. We can try to explain these phenomena by parallel genetic changes in sound-reproduction and sound-perception mechanisms. However, the assumption that perception structures of the brain are created under the influence of sensory experience is much more natural.

Note also the morphological features of neurons of the nucleus of the auditory system of amphibians, where neurons can form that have been tuned to a certain modulation frequency [17]. Along with numerous neurons for which acicula are either very poorly developed or absent altogether, in this formation, there are cells with a rather branched-out dendritic tree and numerous acicula [63]. Within the considered hypothesis, it is possible to admit that neurons of the latter type are elements capable of being trained.

It is noteworthy that the suggested hypothesis is constructed on an unusual principle: from complex to simple. We do not attempt to create a periodicity detector from elements that do not possess this property, but, on the contrary, from a set of elements already able to tune to a certain periodicity (individual acicula), we extract only a certain subgroup. However,

we will risk assuming that training in neural structures uses this principle more often. We will show, in particular, the sharp reduction in the number of neurons during ontogenesis or, in chicks, a sharp reduction in the number of acicula in neurons specialized to perceive a parent's signal directly after they are fed a signal that results in imprinting [64].

Only recently has direct study begun of the character of long-term plastic changes in neurons after long-term sensory experience. One such study was devoted to researching the formation of reaction to visual influences in the tectum of spur frog. It has been shown in particular that training toward frequently repeating stimuli leads to the reaction to individual stimulus becoming shorter, and it reproduces more clearly the characteristics of the stimulus applied during training [65].

Modeling studies also testify to the fact that synaptic plasticity can very much lead to the formation of time selectivity [66, 67]. Recently, one more modeling study has been published [68], which in its own approach is sufficiently close to that of our study. The authors have also shown how synapses with properties of depression and facilitation can form a neuron/detector of specific periodicity. In our work, we have attempted to show that the characteristics of such a periodicity detector form as result of sensory experience.

Without a doubt, our model is quite a long way from possible real prototypes. So, acicula in any case are not ideal coincidence detectors, as postulated in the given model. It is especially difficult to imagine that before training these coincidence detectors will organize an ordered matrix. The Hebb principle in the model is also presented as extremely simplified. However, it is necessary to consider that plasticity of acicula is confirmed by all the new data. In particular, recently, it has been shown that microtubules can apparently penetrate an intensively stimulated aciculum, amplifying its output [69]. We can state with confidence that the basic postulates underlying our modeling have already been proved in physiological experiments, namely: strengthening of the reaction of acicula at a certain time delay of input signals and an increase in weight of synapses that caused the response of a neuron.

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