Sound-Source Localization by Neural Network Based on Modified Integrate-and –Fire Neuron Model with Autopolarization.

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Abstract

A neural-network model based on the modified "Integrate – and – Fire" neuron (MIFN) [10, 11] with autopolarization to simulate a sound localization at dichotic stimulation is presented. The model consists of two groups of MIFNs, which receive excitatory and inhibitory synapses from the corresponding input elements, making the each MINF like the real E-I neurons [3, 4]. It has been shown that the model can detect a short (up to 40μs) Interaural Time Difference (ITD) by a relation of spikes number between neuron groups. Model prediction about possible erroneous sound location received by analytical study was confirmed in psychophysical experiments at qualitative level.

Keywords: Sound Localization, Modified Integrate–and–Fire Neuron, Interarual Time Difference, Sound Source Coding, Erroneous Sound Source Detection

Introduction

It is well known that the auditory system can detect Interaural Time Difference (ITD) with ~10μs precision for sound source localization. There are several approaches to account for this ability considering that neuron time constant is tens times over of ITD. The dominant hypothesis that is good verified by the experimental finding [1, 2, 3] postulates that short ITD is identified by coincidences detectors, operating with frequency-separated and phase-locked signals [2, 7, 8, 9, 12]. Another approach is based on existence of three specific populations of the neurons are called E-E, E-I and E-O [3, 5, 6]. However there is no full understanding for participation of these three neurons groups in ITD detection, especially E-I ones. The E-I cells are dominant ones (about 75% of recording neurons [5]) and activated by the ipsilateral ear and depressed by the contralateral one. Here is presented a simple neural network model for detection of short ITD, which imitates E-I neuron populations. The model bases on modified “Integrate-and-Fire” neuron (MIFN) with autopolarization (see appendix, http://nisms.krinc.ru/Programmes/NeuroCADv201setup.exe, [10, 11]).

Model

The model contains two groups of MIFNs with the hundred neuron elements per each (Fig.1). All elements of model have randomly chosen parameters in some range (see appendix). Every MIFN has two types of connections (synapses) from input elements, emulating the bilateral auditory pathways [1]. The cells of the left group receive excitatory synapses from the left pathway and inhibitory one from the right, and vice a versa. The synapse parameters may be randomly chosen in some range (see appendix), or fixed in the linearly changing order through all neurons in a group (for quick visual analysis of computer simulation results). The left and right input elements are emulated as a single neuron (MIFN) and can generate independent impulse sequences.

Computer Simulation and Analytical study

The second order Runge-Kutta method (time quantum is equal to a half of minimal ITD, in the most cases 20μs) is used for numerical solution of differential equations of MIFN [10, 11]. Each input stimulus contains usually a couple spikes with various ITD (from –20 ms to +20 ms), emulating an activation of the real neuronal auditory system by short snick with bandwidth spectrum. At computer simulation, responses of each neuron group are determined during 100 ms after input stimulus. The network is reset after every stimulation session.

Preliminary testing has been shown that the left and right neuron groups have separate minima of activity (near +1ms and –1ms correspondingly). So, here is presented the results of detailed simulation at short ITD (less then ±1ms). Fig. 2a,b illustrates network responses under varying stimulus ITD. It is seen that ITD decreasing or increasing results in corresponding changes of "concurrent" groups activity shapes. The averaged spike numbers in these neuron groups are indicated in Fig. 2c,d. The ITD code can be determined as a relation between number of spikes occurred in groups, for example it is equal to 1.85 for ITD -960μs, and 0.71 for ITD +400μs. Similar results were obtained at simulation of each input stimulus as the spike bursts (100 Hz – 1 kHz frequency).

In order to understand how the presented model can detect ITD, let us to consider single simplified Integrate-and-Fire neuron (Fig. 3a) from either group. It is described by:

$$\tau \frac{du(t)}{dt} = \left(i_e - i_i\right) - u(t) \ , \qquad (1)$$

where: i_e and i_i are excitatory and inhibitory input currents, τ - time constant, $u(t)$ – the membrane potential. Let us consider for simplicity the case when i_e and i_i are square pulses, with Δt - delay, I_e and I_i – amplitudes and τ_{se} and τ_{si} – durations of excitatory and inhibitory pulses of synaptic currents correspondingly. If $I_e > I_i$, $I_e - I_i > u(t)/\tau$, $\tau_{si} > \tau_{se}$ and i_e pulse is preceded i_i pulse (Δt<0), the $u(t)$ is maximal at the $t = \tau_s$; or if i_e is followed by i_i ($0 < \Delta t < \tau_{si} - \tau_{se}$), at $t = \Delta t + \tau_s$. The simple solution of (1) is as follow:

$$u_{\max}=\begin{cases} u(\tau_{se})=I_e\left(1-\exp\left(-\frac{\tau_{se}}{\tau}\right)\right)-I_i\left(1-\exp\left(-\frac{\tau_{se}-\Delta t}{\tau}\right)\right) & \text{if } \Delta t<0 \\ u(\tau_{se}+\Delta t)=I_e\left(1-\exp\left(-\frac{\tau_{se}}{\tau}\right)\right)-I_i\left(1-\exp\left(-\frac{\tau_{se}+\Delta t}{\tau}\right)\right) & \text{if } 0<\Delta t<\tau_{si}-\tau_{se} \\ u(\tau_{se}+\Delta t)=I_e\left(1-\exp\left(-\frac{\tau_{se}}{\tau}\right)\right)-I_i\left(1-\exp\left(-\frac{\tau_{si}}{\tau}\right)\right)\exp\left(-\frac{\tau_{si}-\Delta t-\tau_{se}}{\tau}\right) & \text{if } \tau_{si}-\tau_{se}<\Delta t \end{cases} \qquad (2)$$

As it follows from (2), u_{max} depends on the synaptic potential duration, time constant of integration elements, the weights of excitatory and inhibitory connections (i.e. synaptic currents), and delay between of input signals (i.e. ITD). The family of $u_{max}(\Delta t)$ curves is depicted on Fig. 3b. It is seen that only the neurons with $I_e >> I_i$ can achieve the threshold at short ITD; the new neurons are involved in firing activity under ITD increasing. So, a number of firing neurons in groups can encode an ITD modulus. Besides, $u_{max}(\Delta \mathrm{t})$ for the neurons from "concurrent" groups have symmetric minima because the same input element exert excitatory influence on the first group and inhibitory one on the second (i.e. $+\Delta t_r$ for the right group is correspond to $-\Delta t_l$ for the left group). The location of these minima (2) configure a range of Δt (between the minima) where exact ITD detection depends on a number of elements in an groups. So, a relation between spikes number can encode the modulus and sign of ITD.

Let us to consider a case when the threshold or membrane potential has shifted. As it follows from Fig. 3b, such shift influences on the number of firing neurons. So, erroneous ITD encoding is possible in this case, namely increase of the threshold or decrease of the membrane potential result in network determination of the given ITD as a shorter one, and vice a versa. Autohyperpolarization (AHP) or long inhibitory postsynaptic potential (LIPSP) have similar but more complicated influences on ITD encoding. For the case of repetitive presentation of stimuli couples the influence of AHP and LIPSP can be displayed (Fig. 4. a - c). These results are received during network stimulation by several couples of stimuli at various intervals between repetitive stimulus pairs. Fig 4d have quantified the results presented in Fig 4 a – c. Besides it illustrates order shifting and error of ITD coding while decrease of interstinuli interval. We have attempted to verify this phenomenon in psychophysical experiments.

Results of psychophysical experiments

The normal volunteers (n=18) were tested at dichotic sound stimulation while presentation of repetitive stimulus sequences. During the testing, couples of short snicks (22 μs) with bandwidth spectrum were presented through headphones. ITD between the stimuli in each couple was fixed, each experimental session included five stimuli presentations with ITD +900μs and ten ones with ITD –900μs. Repetitive couples of stimuli were used with various interstimulus intervals (50ms, 100ms, 200ms, 300ms, 400ms, 500ms, 600ms, 700ms, 1s). Volunteer reports about location of each dichotic stimulus are recorded in the azimuth coordinates. The averaged experimental results are presented in Fig. 4d. It is seen that the errors in localization of the perceived stimulus are increased with falling of interstinuli intertal.

Conclusions

The results of computer simulation and analytical study are shown that presented model based on two concurrent groups of MIFNs each of them is similar to the real E-I neurons [3, 5] can detect a short (up to 40μs) ITD with high precision. Exact ITD coding in the model is possible when repetitive dichotic signals are presented with relative long time intervals (more then 1s). If dichotic signals are repeated with shorter delay the erroneous source coding and localization is aroused, and a degree of such errors is increased at time interval reduction between repetitive dichotic stimuli. This model phenomenon was partially confirmed in psychophysical experiments. Some similarity of model and experimental results allows us to propose that erroneous sound-source detection during the human auditory perception may be based on AHP and LIPSP, which are characteristic for the real neurons.

The presented model detects and encodes of ITD on base of integration of excitatory and inhibitory inputs into single neuron, likely the model R Izak et al [4], and estimation of activity concurrent neuron groups. It is proposed that these mechanisms may contribute to sound source detection in the auditory system in addition to well known coincidence detectors [1, 2, 7 – 9, 12]. It is possible that similar mechanisms may participate in short time delay detection between neuronal processes in the other neuronal systems, for example in the visual and cerebellar cortices.

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Appendix

MIFN [http://nisms.krinc.ru/Programmes/NeuroCADv201setup.exe] is two-compartment model with additional blocks for adaptive threshold and spike generator. The main compartment is single integrate-and-fire [1] model with fixed time constant. The second compartment is an integrator used for emulation of autopolarization and injection of the current in the main one. The threshold has the fixed and adaptive components, the last one is determined on the base of integration the membrane potential of main compartment. In the model described in the present paper, the following ranges of parameters are used: time constant of major integrator: 5 – 7.5 ms; major integrator capacity: 15 – 20 pF; coupling impedance: 58 – 98 Mom; additional integrator capacity: 25 – 37 pF; amplitude of elementary autopolarization: –10 mV; threshold fixed component: 6 mV; threshold rising and falling time constants: 0.5 – 0.7 s.

The whole synaptic current is described as a sum of single synaptic currents injected into the main integrator. The current injected by single synapse depends on synaptic weight and amount of the mediator in synaptic gap. The mediator influx and flow is defined by two separate time constants. The following parameters are used: for excitatory synapse weight: 290 – 770 pA; influx time constants*:* 2 ms; flow time constants*:* 3 – 5 ms; for inhibitory synapse: weight: -540 – 200 pA; influx time constants*:* 3 – 4 ms; flow time constants*:* 30 – 50 ms.

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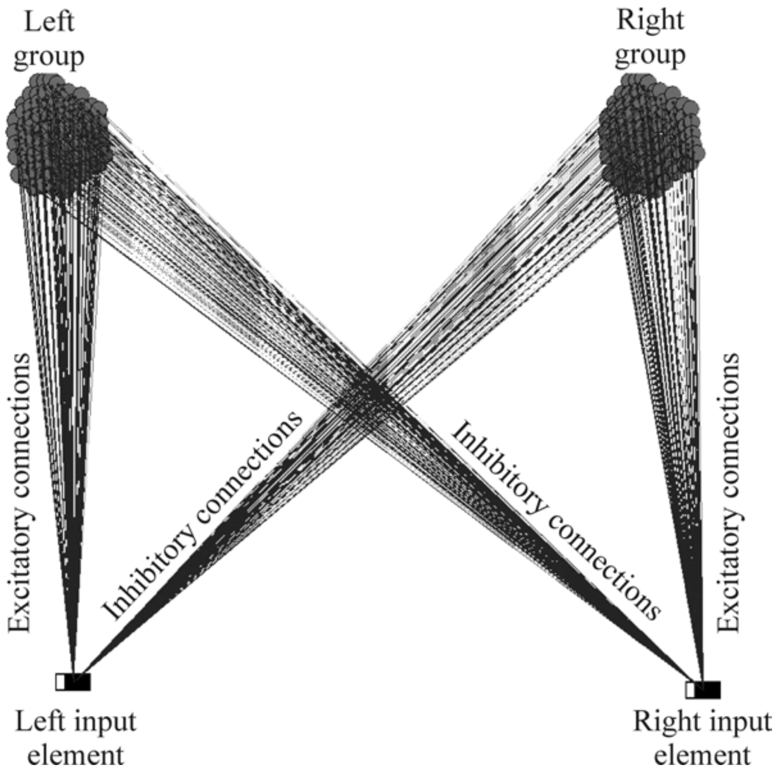


Fig.1 Scheme of neural network model to detect a short ITD. Each concurrent neuron group (left or right) contains a hundred MIFN. Left and right input elements emulate the auditory pathways before the neuronal structures detected ITD. Every input element inhibits the neurons of the contralateral group and excites the ipsilateral one.

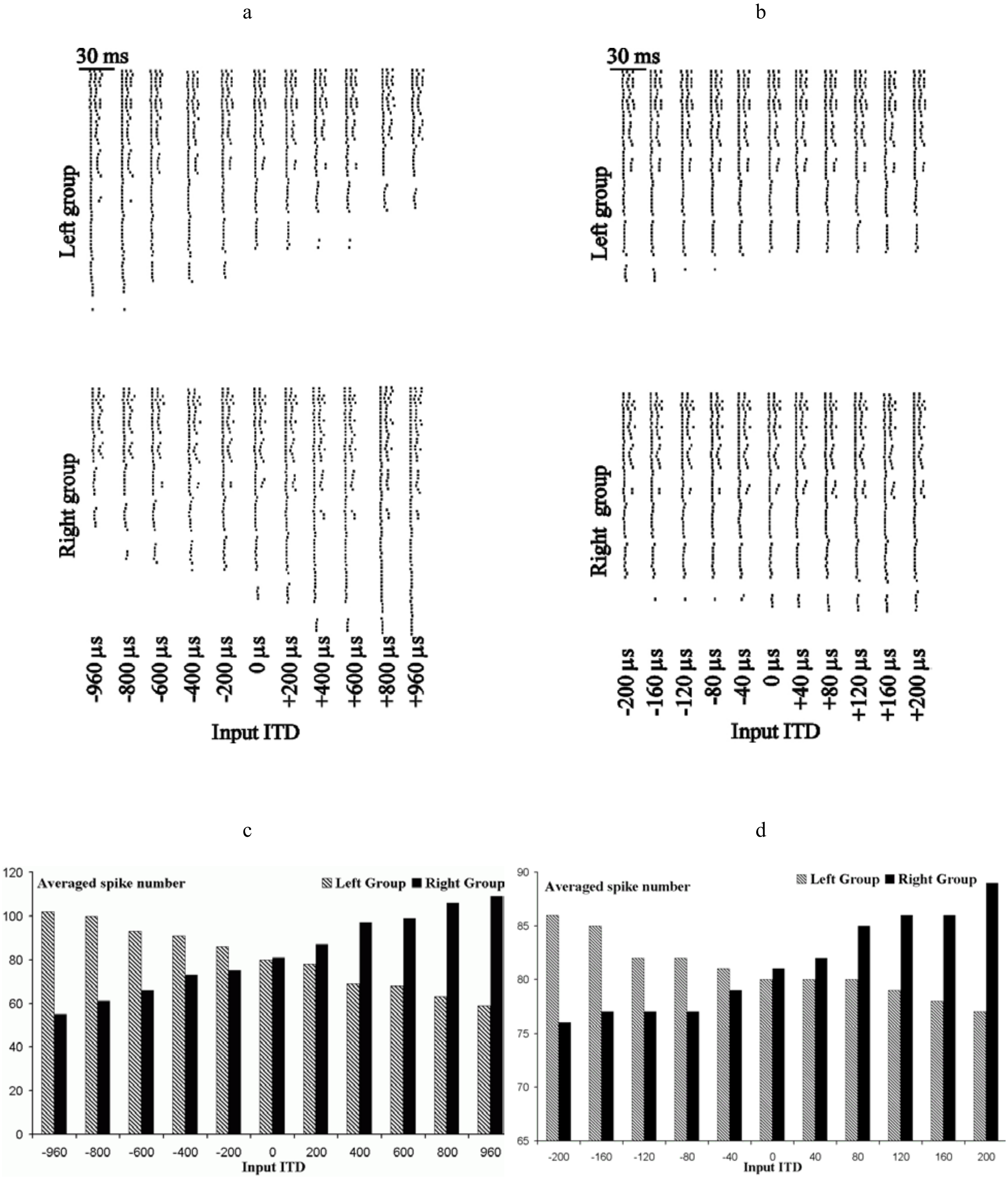
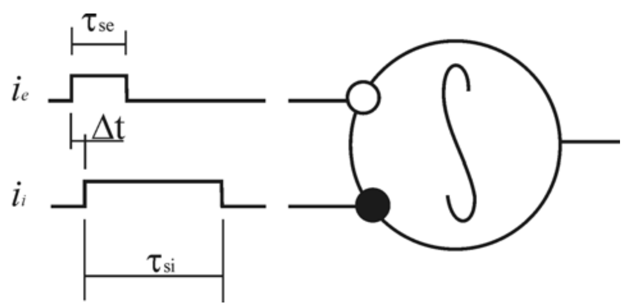


Fig.2 a, b. The responses of neural network model in space of ITD delay (at two scales). Each dot indicates a firing (having the spike) of the corresponding MIFN. (c), (d) show the averaged spike numbers in each group.

a



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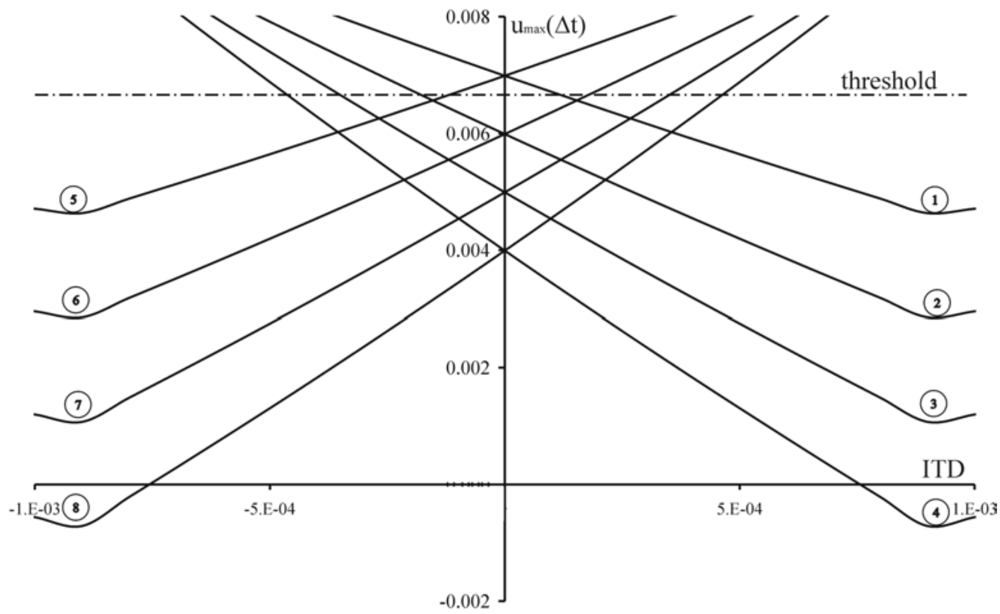

Fig. 3, a. Differential input of Integrate – and – Fire neuron. (b) the value of maximum *u(t)* plotted versus ITD; family of curves is presented for two neurons groups at various relations of I_i/I_e: namely: (1), (5) - 0.3; (2), (6) - 0.4; (3), (7) - 0.5; (4), (8) - 0.6; (1) – (4) – for the left group; (5) – (8) – for the right one. For all curves time constants are equal to: τ = 7ms, τ_{se} = 1ms, τ_{si} = 1.9 ms.

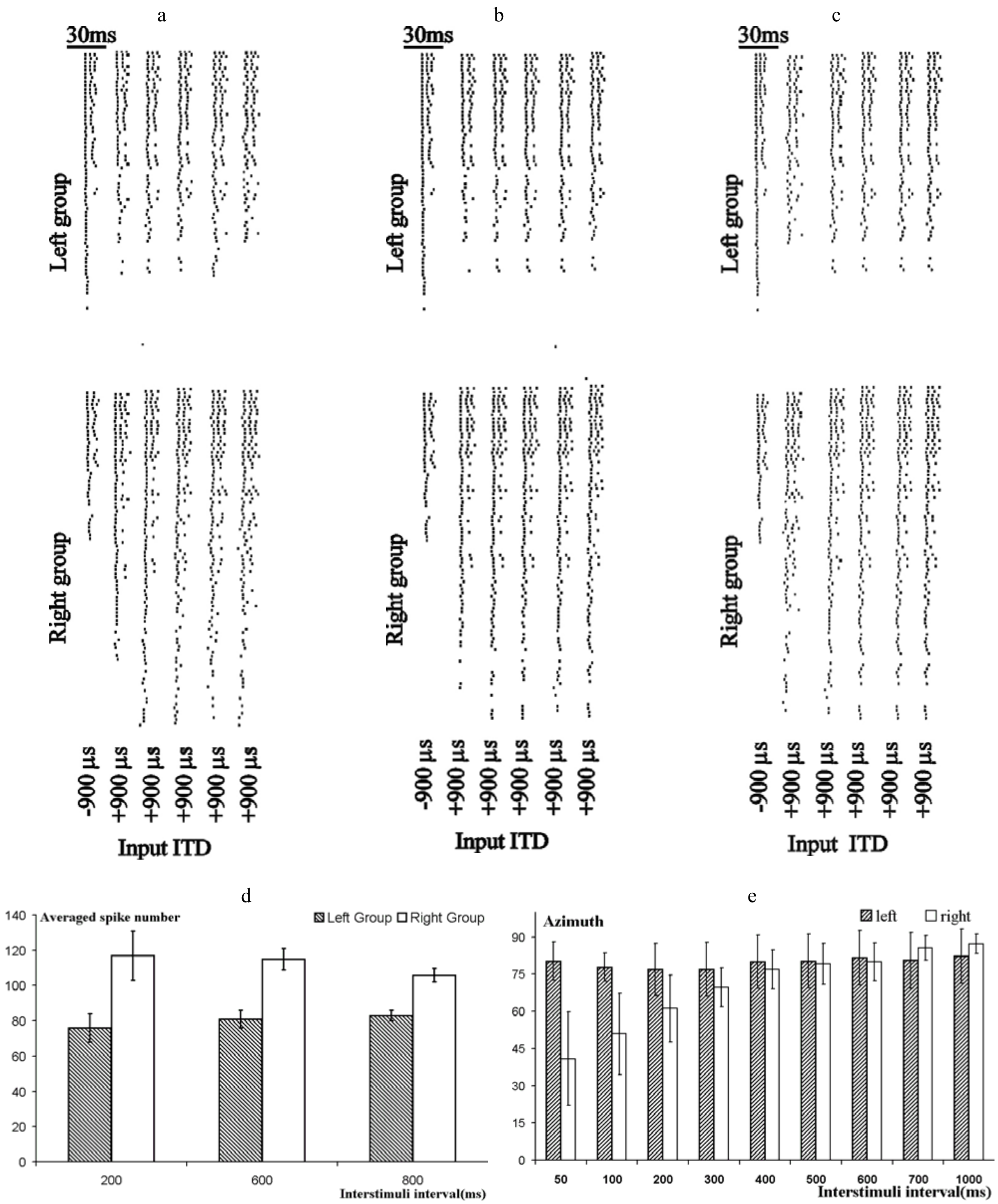

Fig 4, (a) – (c). The examples of neural network response under repetitive presentation of stimulus couples; interval between couples is equal to: (a) – 200ms, (b) – 600ms, (c) – 800ms; (d) averaged spike number and ITD detection errors (vertical segment) for each group; (e) the averaged results of psychophysical experiments; azimuth and error of the perceived dichotic stimulus are presented for the left (+900 µs ITD) and right (-900 µs ITD) sequences.

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