Temporal Patterns Recognized by a Network of Coordinated Time Delays and Coincidence Detectors

J. Pavlásek

Institute of Normal and Pathological Physiology, Slovak Academy of Sciences, Bratislava, Slovakia

Abstract. A computational model of a neuronal network is described which performs a fundamental task of general perception: recognition of temporal patterns in continuous and uncued neuronal spike trains. The presented network is able to recognize each pattern element (100 ms interval composed of sets of 10, 20, 30 and 40 ms interspike intervals combined in linear order) as it arrives. Its operation is based upon biologically plausible filtering mechanisms and population neurodynamics.

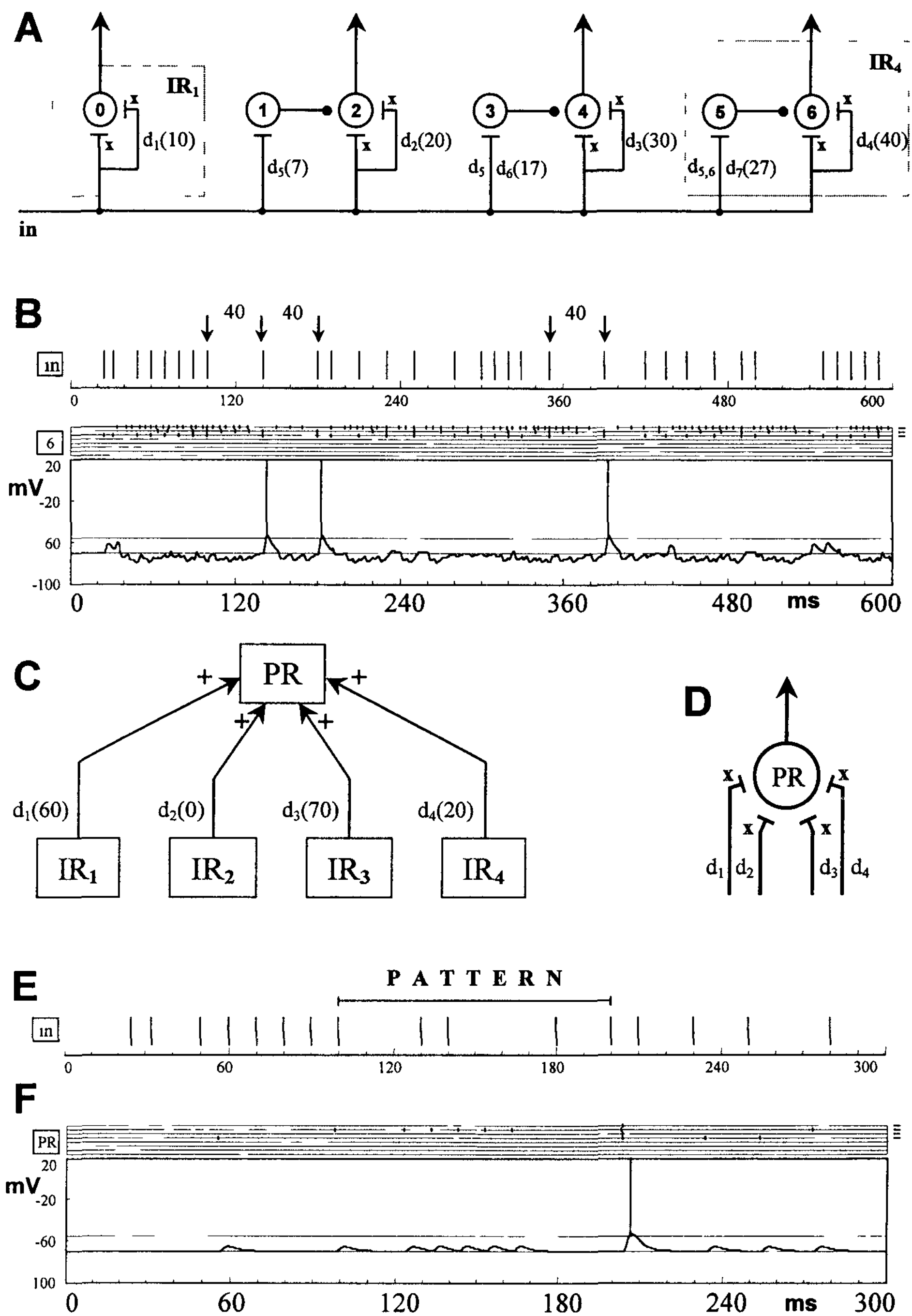
Key words: Temporal patterns — Spike trains — Pattern recognition — Neuronal networks — Computational model

Introduction

Any higher organism of the animal kingdom faces an important task – extracting information about an unknown time-dependent stimulus from segments of a spike train. The fundamental problem of general perception is how can a neural network identify a specific temporal pattern within the continuous stream of pulsatile input activity. It is evident that the recognition task should be connected with functional changes in a set of elements over time which can be used to define pattern. Some ideas originating in both experimental and computational biology advocate the assumption that possible recognizing mechanisms should comprise an "assignment clock" to label stimulus event as having occurred at a particular point in time (Port et al. 1995).

In the present work, temporal pattern recognition is based upon transition of an interval code to the activity of an ensemble of spatially distributed elements (population code, place-cell code) with their responses scattered in time. As simulation experiments have shown, the devised model network by itself figures out a specific pattern (process of segmentation) (Ghosh and Deuser 1995) without its start and end being cued.

Correspondence to: J. Pavlásek, Institute of Normal and Pathological Physiology, Slovak Academy of Sciences, Sienkiewiczova 1, 813 71 Bratislava, Slovakia. E-mail: `unpfpavl@savba.sk`


A
IR1
d1(10)
d5(7)
d2(20)
d5
d6(17)
d3(30)
d5,6
d7(27)
d4(40)
IR4
in
B
40
40
40
C
PR
d1(60)
d2(0)
d3(70)
d4(20)
IR1
IR2
IR3
IR4
D
PR
d1
d2
d3
d4
E
PATTERN
F
mV
ms

Materials and Methods

Model neuron (neuroid) JASTAP has been described in detail elsewhere (Jančo et al. 1994; Pavlásek 1997, 1998). It obeys the principles concerning the physiology of a biologically realistic neuron with chemical transmission of information. The computer program JASTAP can define a network by simple command language and simulates its activity in discrete time intervals (0.5 ms steps). Samples of simulated activity are presented in the form of intracellular recordings.

Results

The temporal pattern was defined as a limited set of different interspike intervals combined in linear order. The devised recognizing network computes the constituents of a pattern (interspike intervals) and consequently identifies the whole pattern as it arrives; the conversion of the time history (an interval code) to propagated responses of the intervals recognizing and pattern recognizing neuroids (place-

Figure 1. A network recognizing temporal pattern. *A*. A model network consisting of 7 model neurons (neuroids 0–6) and one input (in). Connections marked by bars (dots) are excitatory (inhibitory); the crosses indicate subthreshold excitatory influence. The neuroids in frames represent two micronetworks performing the function of the interval recognizers for 10 ms (IR_1) and 40 ms (IR_4) intervals. The afferent activity delays (d_1 – d_7) are in ms (numbers in the brackets). There are two (three) afferents to neuroid 3 (5). *B*. In the upper part there is a raster display of the spikes (SP) (vertical bars) arriving in the network (part *A*) via the input (in); except the first and second interspike interval (7.5 ms and 17.5 ms) all others are 10, 20, 30 and 40 ms long (the arrows indicate 40 ms intervals). In the lower part there is simulation of intracellularly recorded postsynaptic potentials – PSPs (neuroid 6, part *A*). The eight horizontal lines above the simulated recordings represent possible synaptic inputs and the small vertical bars superimposed on them indicate SPs arriving in the synaptic ending (active inputs are marked by short horizontal bars on the right-hand side). The dotted horizontal line is the threshold level for SP generation (vertical bars on the simulated recordings). The dash-dot-dot horizontal line represents resting transmembrane potential; upward (downward) deflections simulate excitatory (inhibitory) PSPs. Abscissa, simulation time in milliseconds; ordinate, simulation of the transmembrane potential in millivolts providing an approximate range of PSP and SP amplitudes in a biologically realistic neuron. *C*. Simplified schematic illustration of four interval recognizers for 10 (IR_1), 20 (IR_2), 30 (IR_3) and 40 ms (IR_4) intervals connected via delay lines (d_1 – d_4) with a pattern recognizer (PR). Numbers in the brackets are delays in ms. Plus signs indicate the excitatory influence. *D*. Four pathways originating from (IR_1) – (IR_4) with delays (d_1 – d_4) (see part *C*) make synaptic connections with a neuroid performing function of the PR. Each path excites the indicated neuroid with subthreshold intensity (crosses), therefore the propagated response (SP) is set up only when spatio-temporal summation of all four excitatory PSPs occurs. *E*. The raster display of the SPs (vertical bars) arriving via the input (in) in the network (part *A*); the pattern consisting of four interspike intervals (30, 10, 40 and 20 ms, horizontal bar) is part of a larger spike train. *F*. The pattern illustrated in *E* evokes propagated response (SP) of the PR neuroid (presented in part *D*); other symbols as in *B*.

cell code) occurs. In the presented simulation experiments each specific temporal pattern is identified by a particular pattern-recognizing neuron.

The devised network is of hierarchical structure. An interval recognizer (IR) is a building block at the input level (Fig. 1*A*). The structural and functional constituents of the IR are simple: the core structure is one neuroid supplied with an input ramified into two parallel paths (divergence), both making synaptic contacts with the indicated neuroid (convergence). The afferent activity spreads with a longer delay in one branch (delay line). Each path excites the indicated neuroid with subthreshold intensity, therefore the propagated spike is set up only when temporal summation of both excitatory influences occurs (coincidence detection). Thus, the delay together with the mechanism of coincidence detection determine the duration of the recognized interspike interval. Delays of 10, 20, 30 and 40 ms were used in the presented simulation experiments. The micronetwork indicated above with a specific delay (e.g. 40 ms) does not detect only "pure" interval (40 ms) but also combinations of shorter consecutive intervals the sum of which equals 40 ms (e.g. 10+10+10+10, 10+30). Therefore, the IRs for detection of 20, 30 and 40 ms intervals were equipped with inhibitory neuroids (feedforward inhibition) (Fig. 1*A*), which eliminate the influence of all combinations of shorter intervals. Fig. 1*B* illustrates the responses of the IR which detects 40 ms intervals in a continuous flow of the afferent pulsatile activity. In technical terms, such IR represents a frequency filter tuned to 25 Hz frequency.

According to the adopted time-pattern definition (see above) the pattern recognizer (PR neuroid) forming the next level has to detect a set of different interspike intervals combined in a linear order. In the illustrated simulation experiments the pattern duration equaled 100 ms interval. The structure of the PR is shown in Fig. 1*C,D*. The information from several IRs (four in this case) is transmitted in parallel pathways which converge on one PR neuroid; the activity in individual paths is conveyed with different delays (delay lines). Each path excites the indicated neuroid with subthreshold intensity, therefore the propagated spike in this PR neuroid is set up only when spatio-temporal summation of all excitatory postsynaptic potentials (EPSPs) occurs (coincidence detection). The illustrated temporal pattern used for the simulation experiment (Fig. 1*E*) was "hidden" within a continuous stream of spiking activity (for instance a "noise") with 10, 20, 30, 40 ms intervals. It was composed of five spikes (the temporal sequence of four intervals was 30, 10, 40 and 20 ms). In order to secure temporal summation of all EPSPs constituting this pattern, the second spike delineating its first interval (30 ms, IR_3) has to "wait" for the last spike of the whole pattern for 70 ms (achieved by 70 ms delay) (Fig. 1*C*). The propagated response of the PR neuroid was generated with a monosynaptic delay after the last spike of the whole pattern arrived. As is evident, the pattern was recognized without its start and end being cued with special signals (Fig. 1*F*).

Discussion

All of an organism's knowledge comes from monitoring of the activity of its own neurons (analog signals and temporal patterns of propagated spikes); processing of time intervals (Pavlásek et al. 1996) as well as frequency change recognition (Král and Majerník 1996) with neural networks is an unavoidable prerequisite for triggering an adequate response. How can the temporal structure of a pattern be extracted out of a continuous spike stream? A variety of different statistical measures have been proposed but mathematics is not natural to elementary neural circuits. It is reasonable to suppose that common computational primitives are involved in low level sensory processing which compute some special features very quickly. "Real-time" processing of interspike intervals must be accomplished at an early stage in the system before timing precision is lost (Casseday and Covery 1995). At next stages it may be translated into a different code that is resistant to degradation across synapses (population code, coded lines) (Konishi 1990). This "bottom-up" processing (with no descending feedback connections) could be done by separate modules performing selective filter operations (Rose 1995). The filtering mechanism implemented in the model network is very simple: the anatomical constituents are represented by divergence, parallel lines and convergence; the functional constituents comprise delay lines, coincidence detection (see also Král and Majerník 1996) and feedforward inhibition. Temporal intervals are represented by responses in an ensemble of spatially specified neuroids (IRs) (population code). A pattern consisting of a set of intervals occurring in a given time relationship can be recognized at the next stage by a processing system which uses delay scatter and again coincidence detection. Time delays in parallel lines are organized in such a way that spikes generated by IR neuroids which transmit information about recognized intervals, although occurring at different times (successive processing), arrive simultaneously at a PR neuroid which then gives a propagated response. Thus, information about a recognized pattern is encoded in the activity of a neuronal throng. The pattern itself represents an "access code" (no cueing is necessary) and pattern recognition taking place through activation of PR neuroids eliminates the necessity of special "search processes". The time window (100 ms) and the lengths of the interspike intervals used in simulation experiments (10, 20, 30, 40 ms) limited the number of disjunctive coverings (distinct patterns) to 401; there is a progressive increase of their number with the interval prolongation.

Distinct streams of processing project through several stages of the brainstem in diverging and converging ways. It is well known that variable signal delays (synaptic, axonal, cellular) along neuronal pathways are omnipresent in the brain (Nowak and Bullier 1997). Computation is not only distributed across the network, but also across time (Longuet-Higgins 1969). Numbers of cells receiving convergent inputs (heterotopic, multimodal) increase in the upward direction (Brooks 1969). A frequent feature is that some of them react more strongly to the same temporal sequence (response specificity) (Barlow 1969); such clearly "tuned" cells (Rose 1995) could play a role of "sequence detectors" or "sequence recognizers" (Granger et al 1995) Increasingly fewer impulses are transmitted, but in more numerous fibers. It can be supposed that part of the purpose of the brainstem circuitry is to create a system of coded lines, delay lines and to establish mechanisms for coincidence detection (Casseday and Covery 1995; Hopfield 1995; Král and Majerník 1996; Pavlásek et al. 1996).

The model network presented herein is able to treat patterns that extend over time and to recognize each pattern element as it arrives. Its operation is based upon biologically plausible filtering mechanisms and population neurodynamics The results of simulation experiments indicate how form creates function; that is, how synaptic connectivity and cellular properties lead to processing algorithms performing identification of temporal patterns.

Acknowledgements. This work was supported, in part, by Slovak Grant agency for science VEGA (grant No 2/5009/99) The authors are indebted to Mrs Ľ Hanulová for technical assistence and to Mrs Ž Gogová to help in the artwork

References

Barlow H B (1969) Trigger features, adaptation and economy of impulses In Information Processing in The Nervous System (Ed K N Leibovic) pp 209—226, Springer-Verlag, Berlin, Heidelberg, New York

Brooks V B (1969) Information processing in the motosensory cortex In Information Processing in The Nervous System (Ed K N Leibovic) pp 231—243, Springer-Verlag, Berlin, Heidelberg, New York

Casseday J H , Covery E (1995) Mechanisms for analysis of auditory temporal patterns in the brainstem of echolocating bats In Neural Representation of Temporal Patterns (Eds E Covey et al) pp 25—51, Plenum Press, New York, London

Ghosh J , Deuser L (1995) Classification of spatiotemporal patterns with applications to recognition of sonar sequences In Neural Representation of Temporal Patterns (Eds E Covey et al) pp 227—250, Plenum Press, New York, London

Granger R , Taketani M , Lynch G (1995) Special purpose temporal processing in hippocampal fields CA1 and CA3 patterns with applications to recognition of sonar sequences In Neural Representation of Temporal Patterns (Eds E Covey et al) pp 183—195, Plenum Press, New York, London

Hopfield J J (1995) Pattern recognition computation using action potential timing for stimulus representation Nature **376**, 33—36

Jančo J , Stavrovský I , Pavlásek J (1994) Modeling of neuronal functions A neuronlike element with the graded response Comput Artif Intellig **13**, 603—620

Konishi M (1990) Similar algorithms in different sensory systems and animals In The Brain Cold Spring Harbor Symposia on Quantitative Biology, Vol LV, pp 575—597, Cold Spring Harbor Laboratory Press, New York

Král A , Majerník V (1996) Neural networks simulating the frequency discrimination of hearing for non-stationary short tone stimuli Biol Cybern **74**, 359—366

Longuet-Higgins H C (1969) The non-local storage and associative retrieval of spatiotemporal patterns In Information Processing in The Nervous System (Ed K N Leibovic) pp 37—46, Springer-Verlag, Berlin, Heidelberg, New York

Nowak L G , Bullier J (1997) The timing of information transfer in the visual system In Cerebral Cortex, Vol 12 (Ed K S Rockland et al) pp 205—238, Plenum Press, New York

Pavlásek J. (1997): Timing of neural commands: a model study with neuronal networks. Biol. Cybern. **77**, 359—365

Pavlásek J. (1998): The binding problem in population neurodynamics: A network model for stimulus-specific coherent oscillations. Gen. Physiol. Biophys. **17**, 323—340

Pavlásek J., Poledna J., Jagla F. (1996): Time intervals comparing neural network. Neural Networks **9**, 1131—1140

Port R. F., Anderson S. E., McAuley J. D. (1995): Toward simulated audition in open environments. In: Neural Representation of Temporal Patterns (Eds. E. Covey et al.) pp. 77—106, Plenum Press, New York, London

Rose G. J. (1995): Representation of temporal patterns of signal amplitude in the anuran auditory system and electrosensory system. In: Neural Representation of Temporal Patterns (Eds. E. Covey et al.) pp. 1—24, Plenum Press, New York, London

Final version accepted August 23, 1999