INFORMATION MODEL OF RESONANCE PHENOMENA IN BRAIN NEURAL NETWORKS

*P. Moos**, *M. Svítek**, *M. Novák**, *Z. Votruba**

Abstract: The paper presents an information model for representation of brain linear and nonlinear resonance phenomena based on information nullors. In the brain functions the rhythms and quasi periodicity of processes in neural networks play the outstanding (significant) role. It is why adaptive resonance theory (ART) including resonant effects has been studied for a long time by many authors. The periodicity in the transfers of signals between the long-term memory (LTM) and short-term memory (STM) creates a possibility of resonance system structure. LTM with information content representing expectations and STM covering sensory information in resonance process offer effective learning. Nonlinear adaptive resonance creates conditions for new knowledge, or inventory observation. In the paper this feature is newly modelled by an information gyrator that best fits these linear and non-linear phenomena.

Key words: *adaptive resonance theory (ART), short term memory (STM), long term memory (LTM), information gyrator, information circuit, information network components, nonlinear resonant feedback*

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1. Introduction

The adaptive resonance theory (ART) has been developed by Stephen Grosberg and Gail Carpenter [6, 8–11]. This theory can be understood as the dynamical description of the information processing in the brain. ART provides a unified systematic perspective for the understanding of periodic processes in interaction of intention and attention in the course cognitive activities. Expectations start to focus on data worthy of learning, and these attentional activities are confirmed when the system as a whole incorporates them into periodical resonant states [2, 5].

For futher investigation it is useful to determine current of information and call it information flow Φ, which is measured in information unit per second. We can analogously define information content I, which determines the quantity of work per information unit [23] or determines the amount of eliminated uncertainity.

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From determination of information flow and information content, one can define other information physics quantities. One of the important quantities can be information power as the product of information flow times information content [19,26].

The information model of the processes between the long-term memory (LTM) and short-term memory (STM) is given on Fig. 1. When a top-down expectation I_1 is flowing to the short-term memory (STM as Φ_1 flow, the bottom-up Φ_2 is bringing the more relevant information content I_1 to long-term memory (LTM).

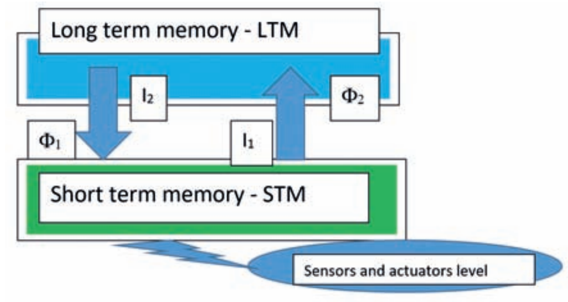


Fig. 1 *Schematic expression of ART.*

The effective interpretation of this information model is determined in the case of resonant process between STM and LTM.

In this paper, the adaptive resonance theory (ART) is studied by using the theoretical information model. In Ch.2 the information model of ART is presented with help of new information components like information transmittance and conductance, information nullor and information norator with the use of concepts introduced in electrical circuits theory. Ch.3 introduces the resonant functional blocks in brain neural structure and Ch.4 introduces two-port representation of the resonant feedback route between STM and LTM. Ch.5 extends this approach to non-linear resonance between STM and LTM that creates condition for a new knowledge, or inventory observation. In Ch.6 the possible applications in very complex uncertain systems are mentioned together with better understanding of emergencies in brain neural networks. Ch.7 brings small example of resonance effect in communication among neural networks.

2. Information circuits

2.1 Electric-information analogies

The electric-information analogies were firstly presented in [23]. The comparison of basic electrical and information variables is given in Tab. I.

Information flow Φ measured in [b/s] defines the amount of information in [bit] transmitted per second. This definition is analogous to the flow of electric charge in electric circuits often carried by moving electrons in a wire.

Information content I measured in [J/bit] determines the quantity of work in [J] done due to available one [bit] of information. It is analogous to an electric potential that represents the amount of work needed to move a unit positive charge

Electrical variables	Information variables
Electrical current [C/s]	Information flow [bit/s]
Electrical potential / voltage [J/C]	Information content [J/bit]
Electrical power [J/s]	Information power [J/s]

Tab. I *Comparison of electrical and information variables.*

from a reference point to a specific point inside the field without producing any acceleration.

In information systems, it is difficult to determine the work in [Joule] and therefore this variable can be specified as a number of excess events that are activated in the system. Information content can consequently be defined as the number of excess events [23] in the system per bit of received information. This means that in order to obtain any concrete information content, we would already have to have done work, such as processing of available information flow, reducing the entropy in received information, etc.

From knowledge of information flow and information content, one can define other information physics quantities. One of the important quantities can be information power PI, defined as the product of information flow and information content. Analysis easily reveals that the unit of information power is work per second realized thanks to the received bit of information. For information systems (IT/ICT), information power is defined as the number of excess events per second caused by the receipt of one bit of information.

By introducing the quantity of information power, one can demonstrate that the impact of information is maximized if the received information flow is appropriately processed by the recipient and transformed into the best possible information content (interpretation). If there is a flow of valuable information that the recipient is incapable of processing, the information power level is low. On the other hand, if the recipient is able to make good use of the information flow, but the flow does not carry needed information, the result is likewise a low level of information power.

2.2 Information model of ART

If the information content I_x is considered as well as a mean for decreasing of entropy in the neural network and in the system decision under the condition of information additivity. Then it is possible to apply the basic principles of the general system theory, as they are expressed, for example in the theory of electrical circuits. The basic approach stems from the description of one information element by equations:

$$\begin{pmatrix} I_2 \\ \phi_2 \end{pmatrix} = \begin{pmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \end{pmatrix} \cdot \begin{pmatrix} I_1 \\ \phi_1 \end{pmatrix} \tag{1}$$

where I_1, I_2 are input and output information content of information segment or branch and ϕ_1, ϕ_2 are input and output data flow, respectively. Let us further expect the all variables in operator form to replace the necessity to use convolution expression in time domain.

The graphical expression via oriented graph and the relation to Eq. (1), as well as respective matrix description are introduced on Fig. 2.

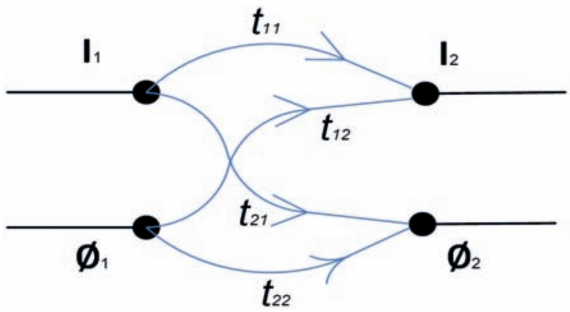


Fig. 2 *Oriented graph representing segment of information network described by Eq. 1.*

In the oriented graph expression on Fig. 2, t_{11} is the transfer function of information content, t_{21} is function of coding, t_{12} represents decoding process and t_{22} is the transfer function of the data (or signal) flow. Coding and decoding process represents the relation between information flow and content

The set of Eqs. (1) can be expressed in matrix form:

$$\begin{bmatrix} I_2 \\ \phi_2 \end{bmatrix} = \begin{bmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \end{bmatrix} \cdot \begin{bmatrix} I_1 \\ \phi_1 \end{bmatrix}. \tag{2}$$

The matrix **T**:

$$T = \begin{bmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \end{bmatrix}, \tag{3}$$

is the cascade matrix describing the "linear" information connection between LTM and STM. Symbols I_i represent information content decreasing the entropy in the approximation of linear dependence on relevant data (signal) flow.

Then:

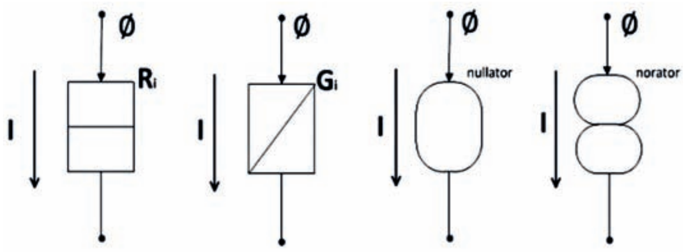
- I_1 is in the model ART input content from STM
- I_2 is in the model ART output content installed in LTM
- Φ_1 is input information flow from STM
- Φ_2 is output information flow to LTM

The schematic expression of the basic components of the information circuit is introduced on Fig. 3. The information model of neural network consists of two-poles [3]:

- transmittance, (is defined as the ratio of I, and Φ)
- conductance, (is defined as the rate of Φ and I)
- nullator, (the input Information content is the same on both nodes)
- norator, (the information content does not depend on the information flow)

These components are described by following graphical symbols and equations:

$$\text{a) } I = R_i \cdot \phi, \quad \text{b) } \phi = G_i \cdot I, \quad \text{c) } I = \phi = 0, \quad \text{d) } I \neq f(\phi).$$



a) Transmittance b) Conductance c) Nullors d) Norators

Fig. 3 *Elementary two-poles of information network without memory behavior in the model of neural structure.*

The detailed meaning of the introduced representation of two-poles is more deeply described in [22, 23]. R_i represents the relation between signal flow and Information content and G_i has the reverse function. Nullators and norators are described by equation c), d) and the meanings of these two-poles are more described in [3, 14–16].

3. Network components of resonant functional blocks in brain neural structure

Let us devote attention to two-ports transforming information content to data (signal) flow and the data flow to information content, as it is represented by branches t_{12}, t_{21} on Fig. 3.

This kind of transforming branches can by represented by two-port matrix description where the nullor representation using conductance G_{21} is presented:

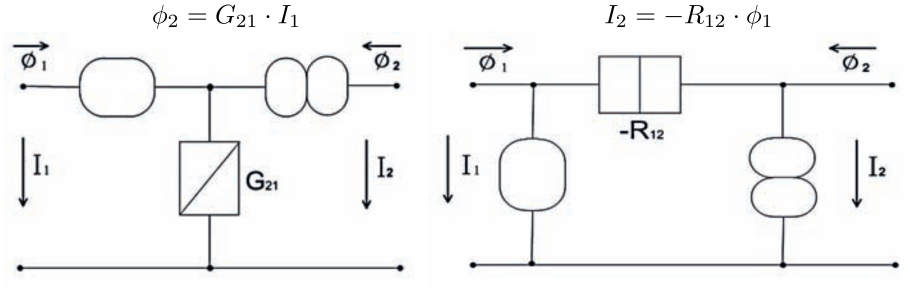
$$\begin{bmatrix} \Phi_1 \\ \Phi_2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ G_{21} & 0 \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \end{bmatrix}. \tag{4}$$

Another representation by the matrix transmittance R_{21} can be written as follows:

$$\begin{bmatrix} I_1 \\ I_2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ -R_{21} & 0 \end{bmatrix} \begin{bmatrix} \Phi_1 \\ \Phi_2 \end{bmatrix}. \tag{5}$$

According [16] Eq. (4), (5) express the function of “controlled sources” as information-controlled source of signal flow, (4) and by signal flow-controlled information content (5). Elementary two-port model structure has the form as it is shown in Fig. 4(a), or Fig. 4(b) [16].

$\phi_2 = G_{21} \cdot I_1$ $\qquad$ $I_2 = -R_{12} \cdot \phi_1$

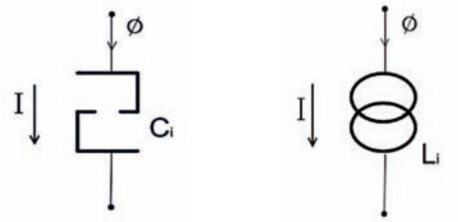


(a) (b)

Fig. 4 *Model of the branch (a) t_{21}, (b) t_{12}.*

For the modelling of STM and LTM it is necessary to work with components having the memory ability – as there are for example “information capacitance”, (Fig. 5(b)) and “information inductance” (Fig. 5(b)).

$I = \frac{1}{C_i} \int_0^t \phi(t) dt$ $\qquad$ $\phi = \frac{1}{L_i} \int_0^t I(t) dt$



(a) (b)

Fig. 5 *(a) Information capacitance, (b) Information inductance.*

The integration shown on Fig. 5(a) and Fig. 5(b) represents the accumulation of information flow or information content in memories STM and LTM.

4. Two-port representation of the resonant feedback route between STM and LTM

If the connection between LTM and STM is approximated as a “parallel” connection of linear two-ports (Fig. 6), and if each two-port is described by “conductance” matrix:

$$\begin{bmatrix} \emptyset_1 \\ \emptyset_2 \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} \\ Y_{21} & Y_{22} \end{bmatrix} \cdot \begin{bmatrix} I_1 \\ I_2 \end{bmatrix}, \tag{6}$$

then the parallel connection can be expressed as the sum of the two-port matrices of each partial two-ports.

$$[Y] = [Y_1] + [Y_2] \,. \tag{7}$$

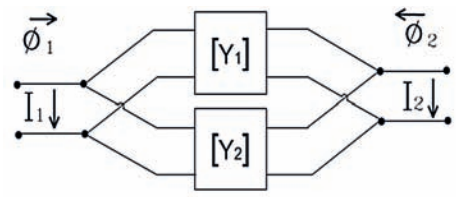


Fig. 6 *Parallel connection of information segments.*

If there is a cascade matrix T available for each two-port, then it is possible to determine the partial conductance matrix in the form [14]:

$$\begin{bmatrix} \frac{-t_{11}}{t_{12}} & \frac{1}{t_{12}} \\ \frac{\Delta t}{t_{12}} & \frac{t_{21}}{t_{12}} . \end{bmatrix} \tag{8}$$

Anti-parallel connection of two-ports from Fig. 4(a) means that input of one controlled source is connected in parallel to the output of the second one (Fig 7).

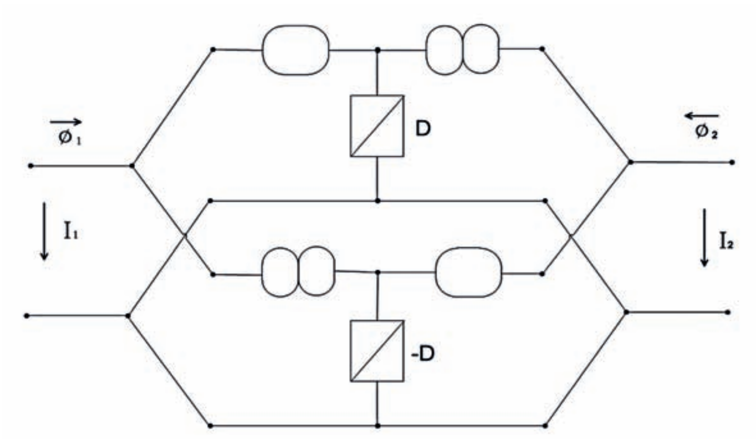


Fig. 7 *Information "gyrator".*

This anti-parallel connection forms the so-called **information gyrator**, which can be described by the conductance matrix in the form [15]:

$$[Y] = \begin{bmatrix} 0 & D \\ -D & 0 \end{bmatrix} . \tag{9}$$

If the output of information gyrator is terminated by the information capacitance of LTM, then the input of this gyrator behaves as an information inductor, (Fig. 8).

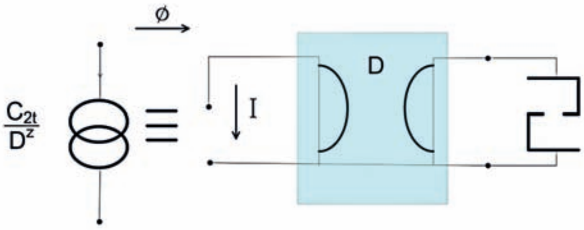


Fig. 8 *Transformation of the memory capacitance into the memory inductance.*

The signal flow Φ in to inductance can consequently be expressed by the equation, which represents the integration (i.e. accumulation of information content in the memory):

$$\emptyset = \frac{D^2}{C_{2t}} \int_0^t I\,(t)\, dt. \tag{10}$$

If this signal flow Φ is connected to STM capacitance C1t, (Fig. 9), then one will obtain the resonant connection with the resonant frequency:

$$f_0 = \frac{D^2}{2\pi\sqrt{C_{1t}C_{2t}}}. \tag{11}$$

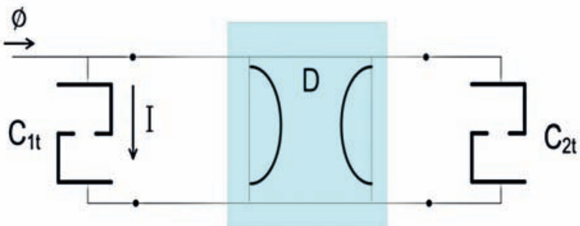


Fig. 9 *Resonant connection with information gyrator.*

The respective resonant curve is in general shown on Fig. 10, where f represents the frequency of information exchanges between STM and LTM.

5. Nonlinear resonant feedback route between STM and LTM

Let the connections between STM and LTM be in principle of non-linear nature (Fig. 11), which is the case that appears quite often. Then it is possible to suppose that matrix relations are valid as well. On the other hand, the matrix elements

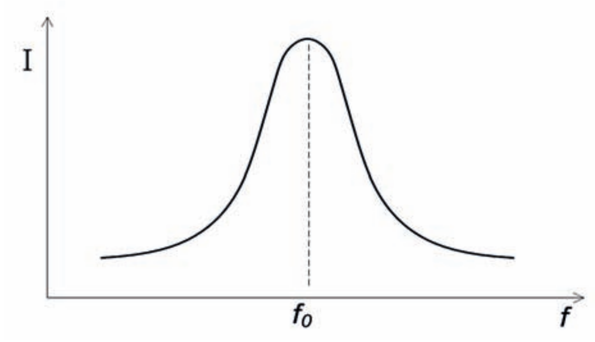


Fig. 10 *The general form of the resonant characteristic.*

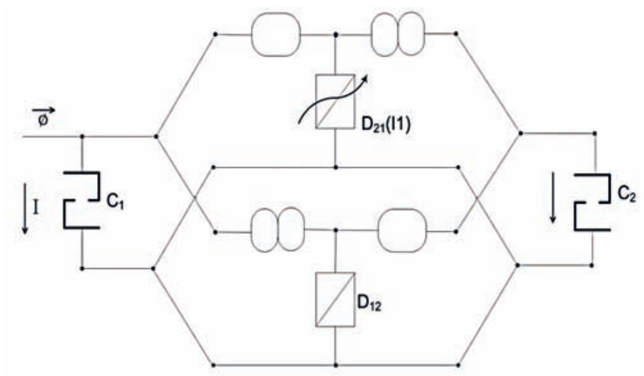


Fig. 11 *A nonlinear model of the relation between LTM and STM.*

become nonlinear functions of their controlling variables. For example, D_{21} is non-linearly dependent on the level I_1.

Then the resonance connection is also a nonlinear one and the resonant frequency can be approximated by the equation:

$$f_0\left(I_1\right) = \frac{D_{12} D_{21}\left(I_1\right)}{2\pi\sqrt{C_{1t} C_{2t}}}, \tag{12}$$

where the resonant frequency f_0 is dependent on the information content I_1 and the respective resonant curve changes its form as it is shown in Fig. 12.

First, one can observe the shift of resonant frequency. In the case where the non-linearity is of higher order this situation projects significantly on the resonant characteristic in which the effect of hysteresis can be observed.

Such effects were already described by R. Thom in his theory of catastrophes [25]. In this paper the meaning of hysteresis in information systems appears e.g. in the connection between LTM and STM, which can be considered as the instant jump in the level of interpretation of incoming signal, quick learning, or even the discovery of new content, generally the emergent phenomenon.

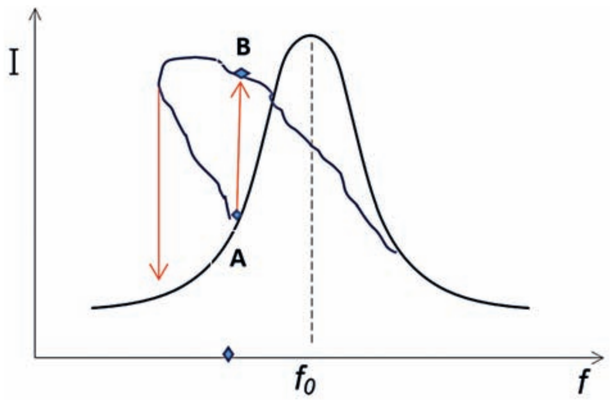


Fig. 12 *The resonant characteristic between LTM and STM with the hysteresis caused by non-linearity.*

In the model of nonlinear resonance effect, the instant jump from point A to point B on Fig. 12 brings the instant increase of information content in LTM and simultaneously in STM. (See experimentally obtained result in Fig. 13)

In principle, this jump can be smooth, but in many practical cases, it can be influenced by some random modulation. However, if this uncertainty is significant one, another apparatus must be used for appropriate system analysis. This kind of behavior is typical namely for large and very complex systems [19].

6. Brain neural networks and resonance

The behavior of very complex uncertain systems can be typical especially for the cases in that respective structures involve significant parts of living bodies. In such a case, the similarity with the above-mentioned operation of LTM and STM functional blocks can form useful base for further investigation.

Thinking about how the information transmission in biological neuron is processed, one has to take into account that information is transmitted through electric synapses principally by bits, however through chemical synapses such information transmission is realized by higher information quanta. These quanta are represented by information content of vesicles, mediators or transmitters (since various names are used for these information carriers, let us further call them simply carriers). At chemical synapses during one directional information transmission between both parts of synapses, many carriers act in parallel.

As far as we know, there is not enough complete knowledge at our disposal about:

- the eventual differences of the information content involved in various parallel acting information carriers especially in chemical synapses,
- the process of information maturing in chemical synapses carriers and of the mechanisms of approaching the threshold level of such synapses,

- the process of combination of particular information coming into chemical synapse via impulses on axon membrane,
- how such complex of information is accepted in the following synaptic part of the cooperating neuron.

Both the transmissions in the electric and the chemical synapses have to be considered a complicated dynamic procedure, the time constants and transmission speeds can change significantly under the influence of other independent variables. Unfortunately, one does not have enough knowledge on it.

As far as the brain is concerned, many problems are still open in operation of the cerebral cortex, the seat of all modalities of higher intelligence [7, 24]. Its organization into layered circuits (often six main layers) has been well known for many years [17]. We also know, that information here undergoes characteristic bottom-up, top-down circulations, and that there exist many horizontal interactions and couplings. How do specializations of this shared laminar design embody different types of biological intelligence, including vision, speech, language and cognition is not however known in detail until now.

7. Small example effect in communication through resonance in neural networks

As was experimentally verified by many authors, for example Hahn, G., Bujan F. A., Frégnatc, Y., Aertsen, A., Kumar, A., the resonant effect can be found in communication processes among brain neural networks. These authors claim in [13], that: "The cortex is a highly modular structure with a large number of functionally specialized areas that communicate with each other through long-range cortical connections". It is has been suggested that communication between spiking neuronal networks (SNNs) requires synchronization of spiking activity which is either provided by the flow of neuronal activity across divergent/convergent connections, as suggested by computational models of SNNs, or by local oscillations in the gamma frequency band (30-100 Hz).

Authors in [24] derive the results, in which slow periodic modulations of the background dynamics could rhythmically improve or even gate signals that propagate using fast oscillations. The fact that the nesting of slow and fast cortical oscillations (e.g., beta-gamma) is commonly found in experiments could be indicative of such a collaborative effort between different cortical rhythms. These results lead us to consider the possibility that top-down signals may provide the change of background activity state required for coherent feedforward oscillations to be generated. The resonance mechanism, which is the essence of the model, is a general property of recurrently connected populations of excitatory and inhibitory neurons [13] and therefore it is widely applicable. Notably, a specific range of propagating frequencies can be achieved by a proper selection of network parameters. In summary, we have shown that communication of neuronal signals across connected networks can be achieved by combining oscillatory activity with resonance dynamics.

Above described nonlinear resonant effect in the neuronal communications is demonstrated in experimental results on Fig. 13, where a jump in the resonant curve is introduced near the frequency 45 Hz.

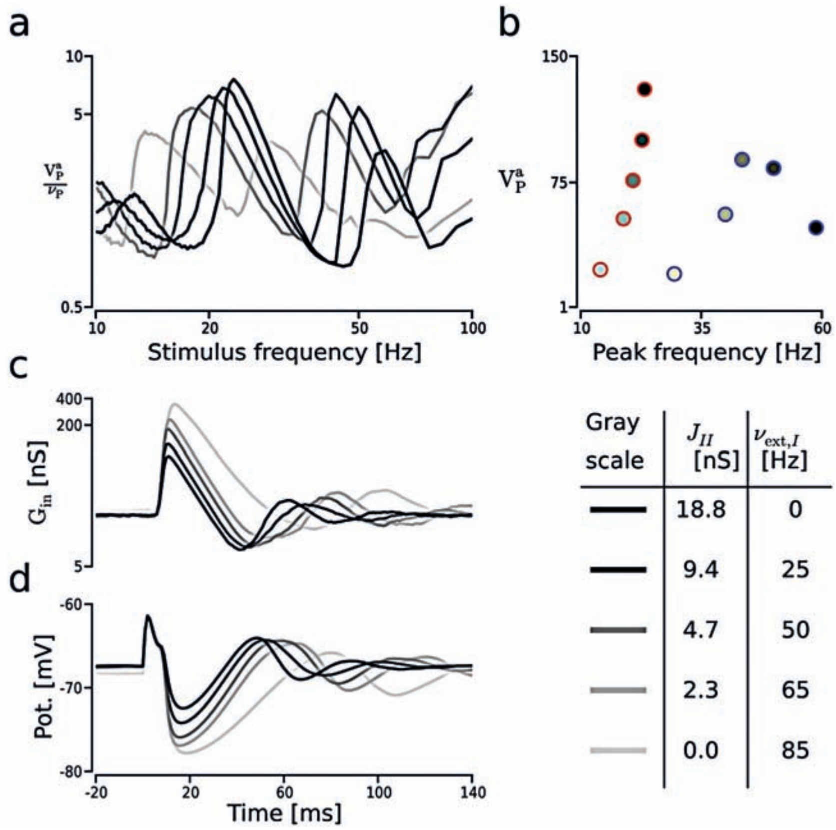


Fig. 13 *(According to authors [13] Responses of isolated layers of neural network in the range of stimulus frequencies 10–100 Hz.*

The reduction of recurrent inhibitory conductance was compensated with an additional external inhibitory Poisson input with a rate as indicated in Fig. 13, where (a) represents the resonance curves for different values. The activity is expressed using normalized by the mean of the spike count vectors calculated with a time bin of 5 ms. (b) Changes in size and frequency of the two main resonance peaks in (a). The points in b) indicate the first (10–30 Hz) and second (30–80 Hz) main resonance peaks, respectively. (c) Pulse triggered average modulation of the inhibitory conductance of neurons for different values. (d) Pulse triggered average modulation of the membrane potential of neurons for different values.

Another set of tasks concerns the investigation of the delicate balance of activities of a rational and emotional nature processed mainly in the left and right hemispheres of the brain, respectively. As far as it is known, this balance, extremely important for brain reliable and safe responses to external stimuli and human interaction with artificial systems, takes place mainly in the prefrontal cortex and can be modified by activities of the amygdala and hippocampus. Though a considerably large research interest has recently been focused on this area, many questions remain open.

8. Conclusion

The introduced information models of processes between LTM and STM in the neural networks of the brain enable the description of the learning under resonance of top-down expectations. The matching of these expectations against bottom-up data, the focus on the expected information flow, and the development of resonant states between bottom-up and top-down processes is properly performed. In the case of resonance, they reach an attentive consensus between what is expected and what is there in the outside world. As Grossberg and others suppose, all conscious states in the brain are resonant states. These resonant states move the learning of sensory and cognitive representations on the higher quality level. The described information model of nonlinear resonance, which summarizes these concepts is therefore called Adaptive Resonance Theory, or ART model. It is necessary to say that ART mechanism seems to be operative at all levels of the sensor system. Simplified models of how these mechanisms are implemented by known circuits of signal flow and information content in LTM and STM are feasible. It is predicted that the same circuit realization of ART mechanisms will be found in the laminar circuits of sensory and cognitive neocortex.

It is also suggested that sensory and cognitive processing in the nonlinear resonance of the brain follow the top-down matching and learning laws that are often complementary to those used for dealing with large spatial and surface transportation systems, or of processing in the brain. This enables our sensory and cognitive representations to achieve the progress in learning more about the input observations, while allow spatial and motor representations to forget learned maps and results that are no longer appropriate. May be the representation by the jump between the A and B points at nonlinear resonance effect could be an appropriate modelling tool. A deeper understanding of these phenomena could help efficiently solving many practical problems, e.g. the task of driver / car simulation and respective virtual environments [1]. We intend to evaluate alternative or mixed approaches, e.g. [21] to gain deeper insight into these phenomena in future research.

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References

[1] BOUCHNER P., HAJNY M., NOVOTNY S., PIEKNIK R. a SOJKA J. Car simulation and virtual environments for investigation of driver behavior. *Neural Network World*. 2005, 15(2), pp. 149–163. ISSN 12100552.

[2] BROWN J.W., BULLOCK D.,GROSSBERG S. How laminar frontal cortex and basal ganglia circuits interact to control planned and reactive cascades. *Neural Networks*, 2004, 17, pp. 471–510.

[3] BRAUN J. Topological analysis of networks with nullators and norators. *Electronic Letters 2*, 1966, pp. 427–428.

[4] CAI Y., WANG J.-Z., TANG Y., YANG Y.-C. An efficient approach for electric load forecasting using distributed ART (adaptive resonance theory) & HS-ARTMAP (Hyper-spherical ARTMAP network) neural network. *Energy*, 2011, 36, pp. 1340–1350.

[5] CAO Y., GROSSBERG S., and MARKOWITZ J. How does the brain rapidly learn and reorganize view- and positionally-invariant object representations in temporal cortex. *Neural Networks*, 2011, 24, pp. 1050–1061.

[6] CARPENTER G.A., MARTENS S., OGAS O.J. Self-organizing information fusion and hierarchical knowledge discovery: a new framework using ARTMAP neural networks. *Neural Networks*, 2005, 18, pp. 287–295.

[7] FROLOV A.A., HÚSEK D., BIRKYUKOVA E.V., BOBROV P.D., MOKIENKOV O.A., ALEXANDROV A.V., Principles of motor recovery in post-stroke Patients Using Hand Exoskeleton Controlled by the Brain-Computer Interface Based on Motor Imagery, *Neural Network World* , 2017, pp. 107–138, doi: 10.14311/NNW.2017.27.006.

[8] GROSSBERG S. A prediction theory for some nonlinear functional-differential equations, II: Learning of patterns. *Journal of Mathematical Analysis and Applications*, 1968a, 22, pp. 490–522.

[9] GROSSBERG S. Some physiological and biochemical consequences of psychological postulates. *Proceedings of the National Academy of Sciences*, 1968b, 60, pp. 758–765.

[10] GROSSBERG S. Nonlinear neural networks: Principles, mechanisms, and architectures. *Neural Networks*, 1988, 1, pp. 17–61.

[11] GROSSBERG S. Adaptive Resonance Theory: How a brain learns to consciously attend, learn, and recognize a changing world. *Neural Networks*, 2012, 37, pp. 1–47.

[12] GROSSBERG S., PEARSON L. (2008). Laminar cortical dynamics of cognitive and motor working memory, sequence learning and performance: Toward a unified theory of how the cerebral cortex works. *Psychological Review*, 115, pp. 677–732.

[13] HAHN G., BUJAN F.A., FRÉGNATC Y., AERTSEN A., Kumar A. Communication through resonance in spiking neural networks. doi: 10.1371/journal.pcbi.1003811, August 28, 2014.

[14] MARTINELLI G. On the nullor. *Proceedings of the IEEE*, March 1965, pp. 332–333.

[15] MOOS P. Aplications of mutators in active RC networks. *Proceedings of the Conference Summer School on Circuit Theory*, Prague, 1994.

[16] MOOS P. Nullor Models of Quasilinear and nonlinear elements, *Studie ACADEMIA 8-83 CAS*, Prague 1983.

[17] NOVÁK M., et al. Artificial Neural networks, C. H. BECK, 1998 (in Czech: Teorie a syntéza umělých neuronových sítí).

[18] NOVÁK M. *Theory of system tolerances*, Academia, 1987 (in Czech: Teorie tolerancí systémů).

[19] NOVÁK M., VOTRUBA Z.: *Theory of System Complexes Reliability*, Aracne edit., Roma, 2018. ISBN 978-88-255-0801-7.

[20] PILLY P.K. and GROOSSBERG S. How do spatial learning and memory occur in the brain? Coordinated learning of entorhinal grid cells and hippocampal place cells. *Journal of Cognitive Neuroscience*, 2012.

[21] PROVINSKÝ P., Floppy logic – a younger sister of fuzzy logic, *Neural Network World*, 2017, pp. 479–497; doi: 10.14311/NNW.2017.27.025

[22] SVÍTEK M. Towards Complex System Theory, *Neural Network World*. 2015, 25(1), pp. 241–247. ISSN 1210-0552.

[23] SVÍTEK M., VOTRUBA Z., MOOS P. Towards Information Circuits, *Neural Network World*. 2010, 20(2), pp. 241–247. ISSN 1210-0552.

[24] SUNG HO JANG, HYEOK GYU KWON Connectivity of Inferior Cerebellal Peduncle in the Human Brain: A Diffusion Tensor Imaging Study, *Neural Network World*, 2016, pp. 439–447; doi: 10.14311/NNW.2016.26.025.

[25] THOM R. Structural Stability and Morphogenesis: An Outline of a General Theory of Models. Reading, MA: Addison-Wesley, 1989. ISBN 0-201-09419-3.

[26] VLČEK J. Systems Engineering (in Czech: Systémové inženýrství), 1999, CTU in Prague ISBN 80-01-01905-5.

[27] WIENKE D., and BUYDENS L. Adaptive resonance theory based neural networks—the "ART" of real-time pattern recognition in chemical process monitoring. *Trends in Analytical Chemistry*, 1995, 14, pp. 398–406.