Pattern Excitation-Based Processing: The Music of The Brain

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Abstract

An approach to information processing based on the excitation of patterns of activity by non-linear active resonators in response to their input patterns is proposed. Arguments are presented to show that any computation performed by a conventional Turing machine-based computer, called T-machine in this paper, could also be performed by the pattern excitation-based machine, which will be called P-machine. A realization of this processing scheme by neural networks is discussed. In this realization, the role of the resonators is played by neural pattern excitation networks, which are the neural circuits capable of exciting different spatio-temporal patterns of activity in response to different inputs. Learning in the neural pattern excitation networks is also considered. It is shown that there is a duality between pattern excitation and pattern recognition neural networks, which allows to create new pattern excitation modes corresponding to recognizable input patterns, based on Hebbian learning rules. Hierarchically organized, such networks can produce complex behavior. Animal behavior, human language and thought are treated as examples produced by such networks.

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1 Introduction

The goal of this paper is to present a theory capable of explaining the remarkable information processing abilities and complex behavior of biological neural networks found in living organisms, particularly in their brains. To accomplish this goal an information processing (computing) paradigm is discussed which is based on the view of the computational process as being an excitation of a system in response to its inputs, similar to the excitation of a particular mode of a string in response to a particular pattern of its initial velocities and displacements. The proposed processing paradigm is different from the one based on Turing machines, and because it is based on excitation of output patterns by some kind of resonators it will be called pattern excitation-based. A generalized machine realizing such processing will be called P-machine. One of the statements of this paper is that any computation achievable with the use of conventional computers based on Turing machines (called here T-machines for brevity) is also achievable by P-machines.

The term resonator is used in this paper to denote an excitable object of some nature which is capable of producing different modes in response to different input patterns. It is not required to be linear, and in fact, non-linearity could be essential for the ability to add new excitation modes to the set of exiting ones. The excitation modes of the resonators discussed here could be changed. The process of tuning of the resonators includes adjustments to the excitation patterns of the existing modes and adding new modes, and can be called learning. Tuning a resonator in a P-machine is similar to re-programming a T-machine-based computer. The property of the resonators of being active means that they can draw energy from sources different from their inputs.

There could be, and in fact exist in the real world, many realizations of P-machines with different levels of complexity, musical instruments being among the "simplest" of them. The realization of P-machines which is of the main interest in this paper is given by neural networks.

The brain’s main information processing cells are neurons, which make numerous synaptic connections with other neurons forming what is known as neural networks. The remarkable abilities of neural networks in respect to pattern recognition are being intensively studied (see books and reviews [1],[2],[7],[13]). It has also been noticed that neural networks are, in principle, capable of performing any computation that a conventional computer can do.

The main power of neural networks comes from the parallel processing of information by very many neurons. But how exactly are neurons organized for the information processing? The well studied neural networks performing pattern recognition function could be considered as passive processing elements. The active elements are given by the pattern excitation networks formed by neurons. The pattern excitation circuits considered here are capable of creating spatio-temporal patterns of activity and are considered to be the network’s main components which code and generate all responses of the network to all potential inputs.

By stating that neurons are organized in the two primary circuit types, one effectively performs what is known in physics as "renormalization", which in this case amounts to replacing fine degrees of freedom represented by neurons with the more coarse grained ones represented by the pattern excitation and recognition circuits. These coarse grained degrees of freedom provide the representation of the nervous system which is more adequate for describing how it works, including behavior and cognition. This transition to the coarse grained picture efficiently reduces the number of degrees of freedom by few orders of magnitude and makes the system much easier to study. Individual neurons, however, still have a role to play: they are wires connecting different parts of the neural P-machine.

One can think of the pattern excitation networks as adjustable, tunable resonators made out of individual neurons, capable of learning and reproducing a number of excitation modes. Various modes of these resonators could be excited by various patterns of stimuli (inputs). The process of tuning the resonators is equivalent to learning by the neural network.

It will be shown below that training of an excitation pattern network could be accomplished by the corresponding pattern recognition network in the supervised learning mode, assuming Hebbian learning in the networks. This leads to the concept of dual pattern recognition - pattern excitation networks, which recognize inputs and generate responses to them.

Hierarchically organized pattern excitation networks can produce very complex behavior and could be responsible for human language and cognition. Some approaches on how that could be accomplished will be considered in chapter [4].
In the computer science language, excitation patterns play the role of different subroutines or procedures called by the main program for processing of various inputs. The main program itself, which often takes the form of an unconditional loop, could be compared to the set of excitation patterns, which control and organize all other excitation pattern circuits. Perhaps even more adequate would be comparison of pattern processing with the object oriented approach in computer science, in which pattern recognition and excitation networks would be direct analogs of objects.

The term neural networks is usually used to describe artificial neural systems. For terminological simplicity in this paper this term will be used for description of both artificial and natural neural systems. Also the words network and circuit will be used interchangeably. The pattern recognition networks will be denoted as PRN, and pattern excitation networks will be denoted as PEN. Since the only realization of P-machines considered in this paper is based on neural networks, the discussion of P-machines will be made mostly in terms of their neural network-based realization.

The work on this paper was largely stimulated by observations that neural networks and brain exhibits some properties of systems studied in the condensed matter physics, particularly by the works [13],[14],[15],[16].

2 P-machines

A P-machine is a mathematical abstraction of the pattern-based information processing. A generalized P-machine is a set of resonators. Particular nature of these resonators is not important here, it could be strings, membranes, resonance cavities of any sort, acoustical, electromagnetic, or other. It is illustrated on Fig. 1 where the set of resonators is called excitable media. The resonators considered here could be active and non-linear, meaning that they could be capable of amplifying particular input patterns, or exciting output patterns not necessarily resembling the input patterns. Each resonator from the set could be excited by patterns of its initial distortion of the corresponding nature. The exact mode of the excitation is the function of the input pattern. This excitation could be thought of as the result of the "computational process" coded by the resonator. Tuning the resonator to a different set of excitation modes could be thought of as re-programming of the resonator. If the modes of the resonators could be changed by the input patterns, then memory could be created in such systems. One of the statements of this paper is that any computation possible by the Turing machine is also possible by a set of tunable resonators, and vice versa. A note is in place, however, that the mapping of one machine into another is not necessarily direct. For this mapping, the work of the Turing machine has to be represented as a set of recognizable patterns capable of exciting other patterns in the corresponding P-machine, so each excitation could correspond to a complex program run on the Turing machine. Vice versa, a single instruction of a Turing machine could be translated in a potentially very complex set of excitation patterns of the P-machine.

Any combination of P-machines is again a P-machine.

Depending on their construction, some P-machines can learn to recognize new input patterns and excite new output patterns. This learning on the one hand is the intrinsic property of the P-machine, and on the other, could require a feedback from its environment. Generally speaking, a P-machine takes its inputs from its environment, and its output could be considered as a change in the environment. This closes the feedback loop, since the next input to the P-machine will be provided by the changed environment. Therefore, continuous operation of a P-machine can result in significant changes to its environment.

To formally describe a P-machine, let us introduce the following notation:

\[ t \] - time
\[ I \] - the input field (example: a set of neurons providing the input to a circuit)
\[ O \] - the output field (example: a set of neurons taking the output from a circuit),
\[ p_I \] - the set of patterns recognized in the input field
\[ p_E \] - the set of excitation patterns produced by the excitable resonators
\[ p_O \] - the set of output patterns of the P-machine
Excitable media

Input patterns

Output patterns

Figure 1: P-machine takes inputs and finds patterns in them which in turn excite corresponding pattern-generating networks. The generated patterns serve as the P-machine outputs.

The computation process by the P-machine could be described by the following set of expressions ($f$ stands for some functions):

$$p_O(t) = f_{OI}(p_E(t)),$$

which means that the output patterns are results of the pattern excitation activity of the machine. In turn,

$$p_E(t) = f_{EI}(p_I(t)),$$

meaning that the excitation patterns are generated by the machine in response to recognized patterns in the input field, and

$$p_I(t) = f_{II}(I(t)).$$

These equations must be supplemented by the machine learning rules describing how the sets of the recognized and excited patterns are changed:

$$p_I = L_I(I, p_E)$$  \hspace{1cm} (4)

$$p_E = L_E(p_I, p_E).$$  \hspace{1cm} (5)

For these equations to be useful in particular applications, all functions $f$ and the learning rules $L_I$ and $L_E$ must be specified.

The correspondence between the pattern processing based machines and Turing machines can be loosely formulated by the following statement.

P-machines are capable of performing any computation a T-machine can perform and vice versa.

To prove that any computation possible by a P-machine can also be performed with a T-machine, one has to write a computer program for a T-machine simulating the P-machine, and to prove that any computation possible by a T-machine is also possible by a P-machine, one has to design a P-machine simulating the T-machine.

This statement says nothing about the efficiency of the maps between the T and P-machines and resources required for the simulations.

One can think of the patterns excitable by the P-machine as corresponding to various pieces of a conventional computer program. For example, an excitation pattern circuit could correspond to a single character, instruction, a block, a subroutine or a whole very sophisticated program.
Hierarchical structure of patterns and P-machines

In the MATHEMATICA book by Stephen Wolfram there is a statement that "Everything is an expression". This paper is largely based on the axiom that Everything is a pattern. An expression is also a pattern. Everything from a single symbol to a very abstract theory could be represented as patterns or patterns of patterns. Even the lack of patterns could be classified as a lack of patterns pattern. But what precisely is a pattern?

In conventional computer science, patterns are defined as extended regular expressions. This definition allows to use finite state machines for finding patterns. But is it possible to define a pattern without reference to expressions, or it is an elementary notion which can not itself be defined? In the later case it is similar to such objects as point, straight line or plane in elementary geometry. One will have to use patterns of some nature to define what is a pattern. The WordWeb dictionary program installed in the author’s computer defines pattern as A perceptual structure. The working definition adopted in this paper is that whatever a P-machine can recognize or produce is a pattern.

Each pattern is made out of elements, which could also be considered patterns and will be called subpatterns. This leads to hierarchical organization of patterns. Generally there is more than one way to identify subpatterns in a pattern, so that one can say that there are patterns of ways in which subpatterns could be identified.

To illustrate this point, let us imagine music made by a pianist playing on a piano. The sounds of music represent excitation patterns of the air recognizable by our ears. Each sound is a result of a motion excitation pattern of a particular string of the piano, yet, it is a subpattern in a passage which is the pattern represented by the sequence of excited strings and strength and duration of each sound, which is produced as the pattern of strokes of the piano keys, each of which is a subpattern of the last pattern. Rearrangement of these subpatterns will lead to a differently sounding passage - the result of different excitation pattern of the piano keys. In turn, passages are subpatterns in melodies, melodies are subpatterns of parts of the composition, and so on.

Similar analysis can be applied to speech and language. Sounds are subpatterns of words, words are subpatterns of small idiomatic expressions, which are subpatterns of phrases, which are subpatterns of sentences, which are subpatterns of thoughts. Thus, thoughts are patterns at a certain level of this hierarchy.

The described hierarchical scheme is not absolute. There could be many feedback loops in the system. For example, our thoughts, choice of words, and sounds are influenced by our desires and emotional patterns acting on all levels of the described hierarchy. Sounds of music affect the emotional state of the pianist, which affects the way he or she plays.

The hierarchical nature of patterns naturally leads to the notion of hierarchically organized P-machines. Bigger P-machines could be made by hierarchically connecting smaller P-machines. In these architecture, subpatterns of excitation patterns of one level of the hierarchy of P-machines become input patterns to the next level P-machines. Existence of feedback loops results in excitation patterns produced by different parts of a P-machine being not completely static and independent, they are influenced by other excitations present in the system, they could be blocked, re-excited or amplified, leading to potentially very complex picture.

One possible organization of the neural network realization of the P-machine corresponding to the described sounds to thoughts hierarchy will be considered in chapter 7.2.

The hierarchical organization described here does not have to be strict. One can imagine constructions in which outputs from what is considered lower level into a higher level P-machine, as well as one level of the hierarchy providing inputs to several levels below.

Assumptions about the properties of neurons and neural networks

In order to introduce the realization (or representation as a physicist would call it) of P-machines in neural networks, let us first consider very general properties of neurons assumed in this paper.

In accordance with the contemporary neuroscience, neurons are excitable cells making many synaptic connections with other neurons, muscles and whatever other cells they are effecting or innervating. The
effects of the neural coupling on the post-synaptic cells could be excitatory or inhibitory, depending on the 
particular connection. In this paper no specific assumptions are made about particular properties of neurons 
outside of what is generally known about them [1, 3, 4, 5]. For example, it will be assumed that neurons 
have a threshold excitation function, but no particular model of that function will be used in this paper, as 
well as no specific assumptions about particular forms of the action potential or firing patterns of individual 
neurons will be made. These considerations could be very important however in discussions of particular 
excitation patterns, patterns stability, reliability of the information carried by the action potential and so 
on.

It will be also assumed that by the virtue of Hebbian learning, which involves adjustments of strength 
of binary interactions between neurons, neural networks can be trained to produce specific output signals in 
response to classes of input signals. This assumption is based on the intensively studied learning in neural 
networks (see for example [1, 3, 4, 5]).

A pattern excitation neural circuit can contain a very large number of neurons, perhaps on the orders of 
$10^4 - 10^8$. When speaking about such circuits, it will be assumed that all mechanisms necessary to make 
excitation patterns stable are present. Among other thing, these mechanisms could include positive and 
negative feedback loops, circuits employing inhibitory synapse and so on. This area currently is not well 
studied, so these assumptions will have to be validated by further research.

Since this paper is concerned with the presentation of a rather general framework, the assumptions made 
are very general. For specific applications of ideas presented here, many specific assumptions about neurons 
and neuron networks will have to be made.

5 Nervous systems as P-machines

This section outlines the main points of the theory that views nervous systems as P-machines.

1. Neurons are assembled into two primary types of circuits: pattern recognition and pattern excitation 
ones. There is no sharp division between these two types of circuits (pattern recognition and pattern 
excitation) and both functions could be represented by the same circuit.

2. Pattern excitation circuits are capable of learning and producing specific spatio-temporal patterns of 
excitations in response to various patterns of stimuli. There could be excitable circuits with different 
characteristic time and spatial scales, producing a wide range of different excitation patterns.

3. Learning of an excitation pattern by a network is in a number of ways similar to learning in the pattern 
recognition networks (for later see for example, [1, 2]). In the approach considered in this paper, the 
learning of excitation patterns is accomplished through a supervised training of the PEN by a PRN, 
and could be based on Hebbian learning (see chapter 6). The pattern generated by the PEN will be 
called dual to the input pattern recognized by the PRN.

4. Potentially a very large number of neural P-machines could be working in parallel, simultaneously 
processing various parts of patterns.

5. Pattern excitation neural networks are hierarchically organized, which allows them to produce complex 
behavior, such as observed in living organisms. In the hierarchical organization, parts of excitation 
patterns (sub-patterns) produce streams of inputs which excite patterns in the lower level networks. 
Sub-patterns of a single pattern of a higher level PEN could produce sequence of inputs for a single 
lower level PEN or simultaneously excite multiple PENs.

6 Learning excitation patterns: recognition - excitation duality

Let us now discuss some ways in which the training of new excitation modes (patterns) could be accomplished. 
Let us connect input of the PRN to the output of the PEN, and the output of the PRN to the input of 
the PEN using neurons sending axons from the PRN to PEN, as shown on Fig.2. Then when there is an input
pattern of the PRN which it can recognize, the output of the PRN will play the role of the pattern presented and the input pattern will play the role of the output shown to the network (PEN) under the supervised training. Because PRN output follows its input, delay d-networks are included on Fig. 2 to insure satisfaction of causality conditions in the training process. If one now assumes that the Hebbian learning is taking place in the PEN, the PEN will learn an excitation pattern which will resemble the input. This PEN will be complementary to the PRN in the sense that the input to the PRN becomes the prototype of the excitation pattern of the PEN, while the output of the PRN becomes the input to the PEN triggering the excitation mode producing the pattern. The direction of connections between the PRN and PEN and, correspondingly the training process could also be reversed, so that the PEN will train the PRN, provided that necessary delay circuits are also included.

Figure 2: Basic learning in the pattern excitation networks is accomplished by connecting the input of PEN with the output of PRN and the output of PEN with the input of PRN. These connections go through (delay) d-networks, so that the pattern recognized by the PRN could serve as the training input for the PEN, and the input pattern of PRN could serve as the output training set for the PEN. The d-networks could play roles beyond the basic delays functions. In fact, they can modify the input to the PRN signal so that the desired reaction by the PEN is actually trained. These modifying functions could be selected by the network hosts using various mechanisms, including evolution through natural selection. Neuron cell bodies are drawn as circles, axon terminals - as triangles.

Another purpose of the d-networks is to alter the input and output of the PRN which are being delivered for the PEN training. By altering the patterns used in training the PEN, it could be taught a wide range of responses to various stimuli. It has to be noted that these patterns could actually be different from the ones experienced by the PRN. The neurons connecting the two networks could themselves be parts of or be modulated by different other networks, resulting in the huge variety of possible excitable patterns stored in the PEN.

One can imagine various scenarios in which the described learning mechanism could be actually implemented in a neural network. For example, a PRN can be training the formation temporary patterns in the PENs serving as a "scratch memory", which in turn could drive the formation of permanent patterns. The permanent PENs would be strengthened with the use and the PRN would also direct which permanent PEN is trained by the scratch memory at any moment of time. This approach is illustrated on Fig. 3. Here new excitation modes for related recognized patterns could be created in the same pattern excitation network.

Let us briefly touch upon the relationship between learning and evolution. Many variations of neural networks organization and learning processes are possible within the proposed framework. For example, d-networks as well as specific reactions of the network to the same outside input could be different, though the participating networks could be trained through the same basic mechanism. These specific reactions and PRN, PEN and d-networks could be subjects of selection through the evolution of organisms. There is also
Figure 3: Different variations of learning of excitation patterns could be considered. In this drawing a temporary PEN is used as a scratch memory. The more a particular pattern is recognized by the PRN, the more permanent PEN learns the corresponding (dual) excitation pattern. In the mean time, responses are generated by the fast learning Temporary PEN. Selection lines can contain many neurons, only one neuron is drawn in each line for brevity.

a possibility that the PENs are "pre-trained" by evolution to the point when little additional training by the PRNs is needed to adjust the function of the PENs to specific environments.

The fact that the pattern recognition networks train pattern excitation networks, which generate reactions of the system to the external inputs, leads to the picture in which both types of networks are complementary to each other. The close relationship between them illustrated on Fig. 2 in which the excitation of the PEN are essentially (modified) inputs to the PRN, allows one to consider the PRN and the PEN as being dual. Structures like the one shown on Fig. 2 could be used as building blocks for more complex networks. Hierarchically organized, such complex networks could be able to perform many functions which are found in living organisms, including language and cognition.

The following remarks are in place.

Though pattern excitation networks are generally capable of learning their patterns, they do not have to learn anything to work. There could exist PRNs which just generate patterns, in living organisms this would correspond to emotions or desires generated without originally learning any patterns. This would be similar to work of cardiac pacemaker cells, which do not need to be excited by an action potential passing by. Existence of such "pacemaker" networks can also be viewed as the manifestation of a different type of learning, which could be associated with biological evolution.

The distinction between pattern recognition and pattern excitation networks is not precise. One can think of the PENs as being PRNs with outputs described by complex patterns. The situation is somewhat similar to the distinction between a program and data in conventional computers, where everything could be treated as data, but one can define the program as being the part of data which is supplied by the programmer, and the "true" data being all the rest. In the case of neural networks the classification appears to be trickier and goes by the function of the network in the neural system. In this case the recognizable by PRNs input patterns can be used to train excitable networks to respond to different inputs. In fact the response could manifest itself as very complex behavior, much more complex than the input that excited it.
7 Examples

7.1 Excitable neural circuits

A simple example of an excitable neural circuit is given in the Fig. 4. Detailed analysis of the excitation properties of neural networks is presented in [6]. Let me note, that the pattern excitation networks under consideration in this paper are not necessarily small, the circuit discussed in this section is chosen as an illustration for its simplicity. Let us assume that the excitatory stimulation of the neuron cell body (drawn as a circle) will generate an action potential propagating along its axon, followed by a short refractory period. A stable excitation traveling counterclockwise could be generated in the circuit by a pulse stimulus from the input neuron $n1$, assuming the excitatory synapse between $n1$ and $n2$.

Figure 4: A simple circuit capable of storing and reproducing excitable patterns on its outputs. In this drawing, the excitation patterns could be triggered by Input1 making excitatory synapse with the neuron $n1$, and modified or blocked by Input2 making inhibitory synapse with $n6$.

The excitation wave traveling in the neural circuit will generate a certain excitation pattern on the output neurons $n01 - n03$. The other input neuron $n2$ could make either excitatory or inhibitory synapse with some neuron, $n5$ in this example. This input neuron ($n2$) has the ability to alter the excitation pattern of the output neurons or even completely block the excitation. Despite of the simplicity of the model, it illustrates the main features of other excitable neural circuits. One can think of the inputs $n1$ and $n2$ as providing the input pattern and the outputs $n01 - n03$ as providing the output pattern which is created by the various excitation modes (patterns) of the circuit. Different spatio-temporal combinations of the input signals will result in different output patterns of activity on $n01 - n03$.

More complex circuits are capable of storing and reproduction of more complex excitation patterns. They could also be controlled in the more precise and sophisticated way than the simple circuit shown in the above example.

It should be noted that the circuit considered in this example is not being treated as a mere memory element, but a computational unit analogous to a subroutine in an computer program. Every time the circuit is excited, a specific "computation" is performed. The result of this "computation" is coded in the excitation pattern output of the circuit.

Pattern excitation neural networks could be hierarchically organized to produce complex behavior. As is was already mentioned, each PEN could be capable of storing and reproducing potentially large number of patterns, which could be consequently excited by a stream of inputs to the PEN consisting of subpatterns.
of patterns excited by a higher level network. Also, in hierarchically organized PENs, a single excitation of the higher level network can supply streams of inputs to potentially large number of lower levels networks.

Figure 5: An example of nesting hierarchical neural circuit topology in which some neurons of the higher level PEN are replaced by whole next level PENs. Excitation circuits $ec_1 - ec_6$ could be also modulated and excited by additional inputs, and have outputs conducting their excitation patterns to other circuits (shown for $ec_1$ only).

Various topologies are possible in concrete realizations such as nesting (Fig. 5), tree and other. Exactly which topologies are realized and how the network hierarchies are formed and trained is the subject of further research.

### 7.2 Language and thought

The approach to the language and thought processing with P-machines, which includes recognition and generation of speech and thought, has to be developed based on the corresponding pattern hierarchy consisting of patterns of sounds, words, sentences and thoughts. Let us first trace the thinking and speaking process from the "bottom-up", starting with making sounds and ending with generating thoughts. At each step of the process there is a set of pattern excitation networks taking inputs from one level of the hierarchy above it and generating inputs for the networks one level below.

1. Sound pattern excitation networks. Excitation patterns produced by these networks are passed to muscles making sounds.

2. Words pattern excitation networks. Excitation patterns of these networks are passed as inputs to sound excitation networks. Subpatterns of word excitation patterns trigger excitation of patterns corresponding to separate sounds. Rearrangements of these subpatterns form patterns corresponding to different words.

3. Stable word combinations, idiomatic expressions and grammar pattern excitation networks. These patterns of combining words into sentences make up grammar, which in described approach is viewed as a set of patterns in which individual words are major subpatterns.

4. Thoughts pattern excitation networks. In this approach thoughts are defined as patterns at this level of the hierarchy. Subpatterns of these excitation patterns provide inputs to the lower levels networks described above.

5. Emotions and desires pattern excitation networks. These could work as pacemakers and moderators starting the whole process or regulating its pace and mood.
Some of the levels could be subdivided into further sub-hierarchies.

This approach is illustrated on Fig. [6]. In the described hierarchy all level are treated as (neural) P-machines, which could have different complexities.

Figure 6: A possible hierarchy of the brain’s pattern excitation networks (PENs) responsible for thought and speech. In this picture, thoughts are the excitation patterns at the top of the hierarchy. Excitation patterns produced by thoughts drive the pattern excitation networks representing grammar, which, in turn, drive the excitable networks responsible for the more fine structured elements of language all the way down to sounds. Neurons mediating feedback and connecting distant levels of the hierarchy are not shown.

This hierarchy should be considered as the dominant structure, however other structures could coexist alongside with it. For example, some subpatterns of lower level excitations could be fed back to higher level networks, while the later could provide inputs to more than the one levels below, which would lead to “context sensitive” speech, and thoughts being directed by the choice of words, or sound of speech.

In addition to the excitation networks, a parallel hierarchy of recognition networks can be drawn, as shown on Fig. [7]. The PRNs shown on this figure are connected to their dual PENs, so that PENs could be trained. The resulting P-machine is capable to recognize its inputs and generate responses to them as
Figure 7: A P-machine capable to recognize its inputs and generate output patterns in response. It consists of pattern excitation (PEN) and pattern recognition (PRN) network hierarchies running in parallel. d-networks allow PENs to be trained by the corresponding PRNs. On this diagram neurons are drawn as arrows showing the direction of the action potential propagation. Each level of the hierarchy recognizes by its PRN and excites by its PEN patterns of the same level in the pattern hierarchy.

output patterns.

Let me note that the recognition process by the hierarchy of PRNs based on the hierarchy of patterns is different from translating computer languages, which is based on ”parsing an expression” [10], [11], [12].

Talking about the human thought, one immediately is faced with its unpredictable nature, which brings up the question: how the seeming unpredictability of thought could be reconciled with the stable excitation patterns approach? This question could be answered in more than one way, and different mechanisms of thought generation could actually be present. Thought generation could be related to (sub) patterns rearrangement and generating new patterns from subpatterns of different patterns, so that new patterns could be accepted and made permanent if they ”pass certain tests” (equivalent to ”are able to excite certain other patterns” in the P-machine language). In addition, the networks’ excitation patterns are modified by many inputs, thus varying the patterns excited at any given time by the same network. These patterns are also excitation modes of the networks responsible for the direction of learning and evolution of thought. At the same time, there is a great deal of stability of such patterns: similar thoughts come to us, as well as similar emotional patterns are excited, in response to similar situations. Also, there seems to be a continuous learning process by the network which results in the excitation patterns being continually modified. This process could also be described by the excitation of patterns, our patterns of learning and patterns (or ways) of thinking appear to be stable over our lifetimes.

Let me stress again that the described language and thought generating hierarchy is presented here as a possibility and to illustrate the theoretical framework suggested in this paper. More research, experimental, theoretical, and computer modeling - based, is needed to understand mechanisms of human language and thought.
8 Generalizations

One of the points of this paper is that an intelligent system could be formed by hierarchies of P-machines consisting of pattern recognition and pattern excitation networks which could be trained through Hebbian learning process mediated by a local binary interaction. The question arises: do there exist systems other than nervous, which are capable of forming PRNs and PENs with Hebbian-like local learning rules? Such systems could in principle exist at different temporal and spatial scales and might not be easily detectable in the human lifetime. Human societies, from small groups to civilizations, and ecosystems could be viewed from such a point of view. Are these examples just parts of a greater hierarchy which at a certain level also includes the human brain? In other words, what other non-linear interactions in nature, apart from the ones mediated by chemical neurotransmitters, could be responsible for formation of intelligent systems at different temporal and spatial scales?

9 Discussion and open questions

1. Experimental status. What would be the experimental strategy to observe P-machines of the brain? Since neuron itself is a P-machine, the question applies to the macroscopic P-machine containing large number of neurons.

Pattern recognition and excitation networks in the brain might be difficult to isolate. These networks could be overlapped, interleaved and entangled in the brain tissues. Moreover, at least in principle, same neurons can participate in many different circuits by switching inputs on and off using different synapses, which could significantly increase the number of excitation (and recognition) patterns attainable with a given number of neurons. This could create difficulties for direct experimental observation of such networks. Still the following questions arise: Can the networks described in chapter 7.2 or their analogs be actually identified in the human brain? Do there exist training delay networks connecting, for example, sound recognition with the sound excitation circuits in the brain which could be observed experimentally?

Other evidence could be based on injuries and ablations. For example, ablations in Wernicke’s and Broka’s areas result in different types of speech and thought impairments. Does it shed any light on the neural P-machine hierarchy organization in the brain apart from the mere location of the impaired functions?

Our numerous experiences tell us that we enjoy certain repeating activities and patterns. Does the reason for this lie in the (resonance) excitation of patterns of activity in the brain? Examples of such resonance excitations would be music, poetry, dancing and other activities with their characteristic repeating sounds and rhythms. Do the consonant and dissonant chords which are characterized by sound frequency ratios equal to certain prime numbers open a window into the workings of the brain? Can excitation modes of some of the brain’s neural networks be characterized by ratios of prime numbers in the ways similar to the mathematical description of linear resonatorls, among them sound modes of strings and membranes?

2. d-networks play an important role in translating recognized patterns into the training sets for excitation networks, not just passive delay elements synchronizing pattern recognition - excitation training processes. Details of this translation are not clear at this time and need further investigation.

3. The notion of scale plays the central role in modern science. It gave rise to such ideas in theoretical physics and mathematics as renormalization and wavelet analysis. What is the analog of scale in the world of patterns? One possible answer to this question is: the number of hierarchical levels in the pattern, which could be considered its complexity. The structure of the Fig. 7 is capable of recognizing complex patterns on its inputs and generating complex responses to them. It scales in the sense that patterns of higher complexity can be handled with correspondingly larger number of levels consisting of blocks of Fig. 2. One can make one more step in determining the brain’s coarse grained degrees of freedom and try these structures for the role of the building blocks of the brain.
4. Two papers considering how people play games were recently published [15], [16], which further substantiate the idea that games are played by humans as pattern excitations in response to patterns recognized in positions, not by mere calculating next moves. This is different from the traditional Artificial Intelligence (AI) approach in which games are played based on the analysis of the position tree arising from different moves. Which approach is ultimately more powerful in situations where computing or network resources are limited is an open question, however the latest chess games between the human world champion and computers show that computers seem to be winning. In my view this could be attributed to the limit of number of specific game patterns the human player comes across during his playing experience, and therefore the number of recognizable game patterns and excitation modes which could be trained over the human lifetime.

5. Emotions represent excitation patterns which have the ability to modify the work of other pattern recognition and generating networks. Subconsciousness could be viewed as the set of excitation patterns, which are excited in response to their stimuli, but which people are not necessarily aware of. These excitations, being modes of non-linear resonators, could give rise to or block other excitations in various parts of the system, leading to various, sometimes undesired consequences [17], [18]. From the point of view of this paper, psycho-analysis is a way to re-train the blocking processing pathways, or bypass them altogether by creating new ones.

6. The number of recognized and excitable patterns in living organisms is limited by the available resources of their nervous systems. Given the average time scale of learning to recognize and excite a pattern, there are only limited number of patterns an organism can potentially learn and excite over its lifetime. The need in the number of patterns is also limited by the lifetime needs of the organism. As new conditions arise in the environment, organisms learn to recognize them and develop new excitation patterns to generate responses. Discovery of new patterns in nature which are important for living organisms is a very laborious process. In the process of evolution new levels of the hierarchy are added to the neural networks to make organisms more adaptable to various environmental challenges.

7. Ideas discussed in this paper could be applied to various fields such as understanding and treatment of mental and neurological diseases, education, artificial intelligence systems and so on. However, for practical applications, many properties of the pattern excitation neural networks and their training will have to be studied in great details. These studies must involve both identification of the pattern excitation networks in nervous systems, analytical investigation and computer simulations of such networks.

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