

Energy-information coupling during integrative cognitive processes

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Abstract

The physical conception of energy is a natural and general approach to describe functional interactions in the brain at different levels starting from studies of molecular interactions up to the integrative studies of cognitive neuroimaging. In this article, we describe the representation of the brain as a fluctuating energy field, which adaptively reflects the environment.

Within this neuroenergetic conception, we indicate a physically solid approach to the problem of the link between brain function and information processing - transmission and integration of information between neuroglial populations is coupled with the corresponding energy increase used for information encoding. We develop the integrative neuroenergetic model of face recognition, in which the input to the model tries to modify the fluctuations of activity according to the free-energy minimization principle corresponding to metabolic efficiency. Once the spatial path of integration in neural activity is known, the processed information can be decoded by spatial differentiation. Energy-based feedback with activity rescaling does not influence the possibility of decoding the information.

The model provides further evidence that the conception of energy facilitates at both the computational and conceptual levels the understanding of brain function and its relation to cognition.

Key words: brain energy; neuroenergetics; integrative activity; predictive coding; free energy

1. Introduction

1.1 Brain energy as a measure of brain function

One can claim that the physical concept of energy is useful in neuroscience because it may provide an interface between the brain and cognition (Strelnikov, 2014a). Indeed, energy characterizes not a physical object itself but interactions between the parts of this object as well as its interactions with other objects. Thus, the conception of energy provides a key to brain function where "function" is considered as a certain interaction between brain parts at any level – from the macroscopic anatomical parts of the brain to the interactions of molecules of the brain. In this article, we consider cognitive neuroenergetics from the experimental and conceptual points of view, then we include the discussed principles into a model. Though some equations are provided in Materials and methods, they can be skipped by a non-computational reader.

Sensory input is a way to perceive changes of energy in the external world. A change of energy in the receptor molecules is induced by the change of energy in their surroundings. During further propagation of sensory information, the initial molecular change of energy is amplified using energy sources of neuroglial populations, mainly glucose, which comes from the blood (see (Magistretti and Allaman, 2015) and (Jha and Morrison, 2018) for the reviews of neuroglial metabolism). It is evident that

starting from receptor molecules the transforming influence of sensory input needs to do some work to change the preceding state of molecules and cells, for example, to change their spatial positions, charges etc. Given that further propagation of this sensory input is supported by energy sources, the biological system needs to minimize its energy expenses (Niven, 2016; Niven and Laughlin, 2008). Comparing the energy needed to produce action potentials for a wide range of channel densities and kinetic parameters in a wide range of neurons from several species, it was demonstrated that the ion channels minimize energy expenditure in their normal range of spiking (Hasenstaub et al., 2010). The authors suggest that energy minimization subject to functional constraints may be one of the unifying principles in the brain. In information theory, a bit is the smallest unit of information, which can hold only one of two values: 0 or 1. It was estimated that it costs 10^4 ATP molecules to transmit a bit at a chemical synapse, and $10^6 - 10^7$ ATP for graded signals in an interneuron or a photoreceptor, or for spike coding (Laughlin et al., 1998). Given such high energy demands for information transmission, the authors concluded that, in noise-limited signalling systems, a weak pathway of low capacity transmits information more economically, which promotes the distribution of information among multiple pathways. Considering energy economy in the brain, Bullmore and Sporns (Bullmore and Sporns, 2012) suggested that brain

organization is shaped by an economic trade-off between minimizing costs and allowing the emergence of adaptively valuable topological patterns of anatomical or functional connectivity between multiple neuronal populations.

On the other hand, the work to change neuroglial activity is minimal when sensory input arrives to neuroglial populations, whose activity has already the closest resemblance to the activity needed to code this input – predictive neuroglial coding. From the neurophysiological perspective, this corresponds to the findings that high energy efficiency is achieved at more depolarized spike threshold (Yi et al., 2015). The system's state retains information about past environmental events, and a part of this information is predictive of future events. The remaining nonpredictive information reflects model complexity that does not improve predictive power, and thus represents the ineffectiveness of the model (Still et al., 2012). Free energy was proposed as a reflection of the resemblance between the predictive coding and the sensory input (Friston and Stephan, 2007). In literature, there is an information theoretic (variational) and thermodynamic (Helmholtz) free-energy formulations of neuroglial processing, which can be related in a fundamental way through complexity minimization as discussed in Sengupta et al. (Sengupta et al., 2013). It follows that the minimization of work needed to propagate and treat

the sensory input corresponds to the free-energy minimization.

Increased energy in the neuroglial population is the same thing as increased activity and can be understood as an increase in the firing rate of neurons, an increase of the electromagnetic field energy or as an increase in oxygen and/or glucose consumption leading to the increase of the regional cerebral blood flow. All of these views are possible because electromagnetic and molecular energies are highly coupled in the brain. With this in mind, we earlier defined the term "activation" for the brain as information-driven reorganization of energy flows in and among populations of neuroglial units, leading to a total increase of energy utilization in these populations. Energy "flows" are coherent spatial and temporal changes in the energy turnover of neuroglial units accompanying information treatment (Strelnikov, 2010). The various, and often indirect, methods of practical measurement notwithstanding, brain activation is best understood as a level of energy in an ensemble of neuroglial units, with different methods more or less accurately reflecting this level.

1.2 Energy amplification as information/energy coupling

The amplification of energy changes starts from the receptor molecules and is needed for several reasons. During integrative processes, there is an increase of information transmission, which is accumulated from

one stage to another in the stream of sensory processing. The information is coded by the interactions between different molecules and their parts leading to the increase of energy at each more integrative stage of processing with respect to the previous less integrative one (Huang et al., 2017; Kukushkin and Carew, 2017; Marx and Gilon, 2012). To understand brain function, it is important to study the coupling between energy amplification and information integration. One can take any small volume of the brain and characterize various interactions of molecules within it as a certain summary level of energy. If for each point (i.e., a small volume of the brain) one attributes a certain energy level, one can consider the brain as an energy field in the physical sense where each point has a certain level of energy. According to the experimental data of neuroelectrophysiology, it is possible to get the energy and energy function of neurons (Wang et al., 2015), and then calculate the neural energy field related to cognitive processes. Further on, one can consider directions of energy changes in time and in space for each point with respect to the surrounding points (Strelnikov and Barone, 2012).

If one considers the summary amount of energy at each integrative stage of sensory processing, the difference in the energy levels between the stages should correspond to the difference in the amount of information coded by neuroglial populations at these stages (Figure 1). This can be considered a

biophysical principle because it is physically impossible that more information content is maintained by the same or lesser amount of energy; the encoding of the high amount of information in the integrative neuroglial populations should lead to the increase in their energy turnover. We modelled this relation by an integrative model, which permits information decoding using spatial differentiation of the obtained activity (Strelnikov, 2014b) and suggested that spatial differentiation of brain activity may be a way to obtain virtual spaces with internal representations. The coupling between energy turnover and information integration was recently demonstrated for fMRI activity where there was an amplification of local changes from low-level acoustic cortical regions to high-level cortical regions that accumulate and integrate information (Yeshurun et al., 2017).

On the basis of thermodynamic reasoning (e.g., (Ortega and Braun, 2013)), it can be shown that changes of free energy are related to changes in information by a simple equation:

$$\Delta F = kT \ln c \quad (1)$$

where ΔF is a free-energy difference, k is the Boltzmann constant and T is temperature. At constant temperature T , kT can be interpreted as the conversion factor between units of energy and information.

Generally speaking, energy is a certain measure about interactions of objects or their parts. From this point of view, it is quite natural that information about interactions of sensory molecules with the external world can be quantified as measurable energy of these interactions. These interactions are further transmitted via measurable energy changes of neuroglial populations. By “measurable” we mean that there is a technical possibility of such measures, even though limitations can exist at the current stage of progress.

However, any energy increase is dissipated with time as heat. Finally, it would lead to the loss of information about the initial change of the receptor energy with a corresponding emission of heat (Landhauer theorem). Dissipation of energy decreases the predictive neuroglial information: there is a fundamental equivalence between the dissipation of energy and the nonpredictive information carried by the system (Still et al., 2012). Thus, the dissipation should be compensated by the energy sources of the body.

A constant increase of energy turnover due to information integration can lead to the required levels of energy, which are beyond the possibilities of glucose and oxygen supply to the neuroglial populations. This explains a large network of feedback mechanisms, which rescale energy differences between the stages of information integration to match the physiological capacities of

energy turnover. Neuroenergetic consideration provides a natural explanation, at least partly, for the necessity of neural feedback.

At each stage of processing, information is analysed with respect to the expected features and the results are transmitted to the neuroglial populations at the next stage. A certain number of energy profiles for predictive coding already exist in the baseline activity fluctuations of the system. Energy minimization means that from these energy profiles, sensory input chooses and reshapes the one with minimal deviation from perceived information.

Importantly, objective information measured in bits should not be confused with subjective information based on previous experience and hardly measurable. E.g., looking at the same picture with the same amount of objective information one person can say “a woman” and another person “my mother”. However, experience is also formed by the objective physical information received in the past.

Most of the existing theories of neural coding are based on electric properties of neurons. At present, it is impossible to evaluate, which of these theories satisfy the above-mentioned principles of energy turnover in the brain (energy minimization, information/energy coupling, energy-based feedback). One needs to evaluate these coding theories on the basis of their correspondence to the energetic turnover in neuroglial populations in

response to energy changes in receptors. To deal with this problem, Wang et al. (Wang et al., 2017) recently calculated neural energy supply and consumption based on the Hodgkin-Huxley model during firing action potentials and subthreshold activities using ion-counting and power-integral model. After introducing a synapse energy model, this line of research could be generalized to energy calculation of a neural network and help estimate neural coding theories in terms of energy turnover. Based on the Hodgkin-Huxley equation, Wang et al. (2018) indicated that the electrophysiological activities of neurons are restricted by the energy levels in the brain and modulated by the balance between energy absorption and energy expenditure. In the Hodgkin-Huxley model of the squid axon, optimizing the kinetics or number of Na⁺ and K⁺ channels can whittle down the number of ATP molecules needed for each action potential by a factor of four (Sengupta et al., 2010). The authors claim that the temporal profiles of the currents underlying action potentials of mammalian neurons are nearly perfectly matched to the optimized properties of ionic conductances so as to minimize the ATP cost. For a single postsynaptic neuron, Moujahid et al. (2011) showed that maximum energy efficiency, measured in bits of mutual information per ATP molecule, requires maximum energy consumption. On the contrary, for groups of parallel postsynaptic neurons the energy efficiency of the transmission presented clear maxima at relatively

low values of metabolic energy consumption. Kostal and Kobayashi (2015) investigated a single-compartment Hodgkin-Huxley type neuronal model under the spike-rate coding scheme and addressed how the metabolic cost and the decoding complexity affects the optimal information transmission. They found that the sub-threshold stimulation regime, although attaining the smallest capacity, allows for the most efficient balance between the information transmission and the metabolic cost. Kim (2018) adopted the Hodgkin-Huxley neurons as biophysical neural correlates that form the basic perceptual units in the brain and used Hamiltonian mechanics to demonstrate the minimization of free energy, which he considered equivalent to the minimization of sensory uncertainty about an unpredictable environment. The biophysical energy proposed by Wang and Zhu (2016) can be used to simulate both the activity of neurons and of large-scale cortical networks.

2. *Material and methods*

We develop here the hierarchical feed-forward model that we proposed (Strelnikov, 2014b), which comprised two networks. The first network consisted of two layers and was trained to perform integration by small parts of the input. The second network consisted of 7 layers and continued the integration: using the rule that the integral of the sum equals the

sum of the integrals, it summed up the results of the first network. These networks perform spatial integration of the presented images (Figure 1).

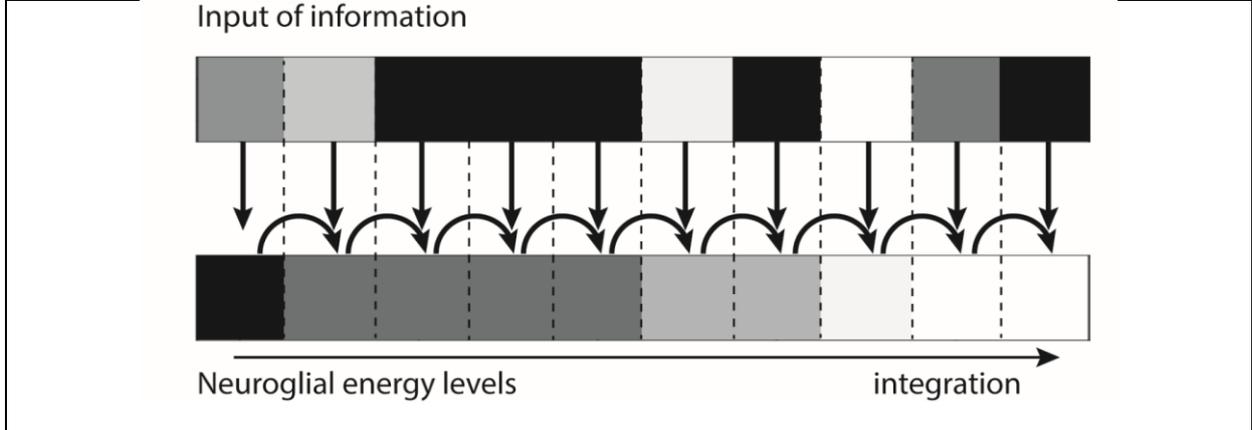


Figure 1. The principle of information and energy coupling during spatial integration.

The scheme illustrates how each new amount of information is added to the existing amount and transmitted further to the other neuroglial population. Each arrow summarizes the ensemble of synaptic and ephaptic inputs from one neuroglial population to another. Different amounts of the input information are colour-coded. An increase in the coded amount of information in each structure is coupled with an increase of its energy (from black to white). The voxel on the right represents the most integrative structure, which receives all the information. It requires the highest amount of energy to code information in molecular structures.

Thus, the activity of this network reflects the information-energy coupling principle. The high performance and reliability of integration by the network made it possible to decode the input images by mixed spatial differentiation of the activity patterns.

Activity in two dimensions, in the point (l,m) given input I(x,y) is calculated as:

$$a_{lm} = kT \int_0^l \int_0^m \ln(I(x,y)) dx dy \quad (2)$$

If activity in 3D, in the point (l,m,n), given input I(x,y,z) is needed, it can be calculated correspondingly:

$$a_{lmn} = kT \int_0^l \int_0^m \int_0^n \ln(I(x,y,z)) dx dy dz \quad (3)$$

The inverse calculations, to restore input from the two-dimensional activity:

$$\ln(I(x,y)) = \frac{1}{kT} \frac{\delta a(x,y)}{\delta x \delta y} \quad (4)$$

If the input was three-dimensional:

$$\ln(I(x, y, z)) = \frac{1}{kT} \frac{\delta a(x, y, z)}{\delta x \delta y \delta z} \quad (5)$$

Equivalently, with gradient projections for two dimensions:

$$\ln(I(x, y)) = \frac{1}{kT} \nabla_x \nabla_y a(x, y) \quad (6)$$

Or for three dimensions:

$$\ln(I(x, y, z)) = \frac{1}{kT} \nabla_x \nabla_y \nabla_z a(x, y, z) \quad (7)$$

The order, in which partial derivatives are taken, does not change the result of mixed differentiation. As gradient functions already exist in Python and Matlab, the gradient approach is easy to implement. The two-dimensional model is presented as the basis to explore its functionality with convenient visualisations.

Here, we present a further development of this model so that alongside information/energy coupling, it includes some other important neuroenergetic principles (Figure 2).

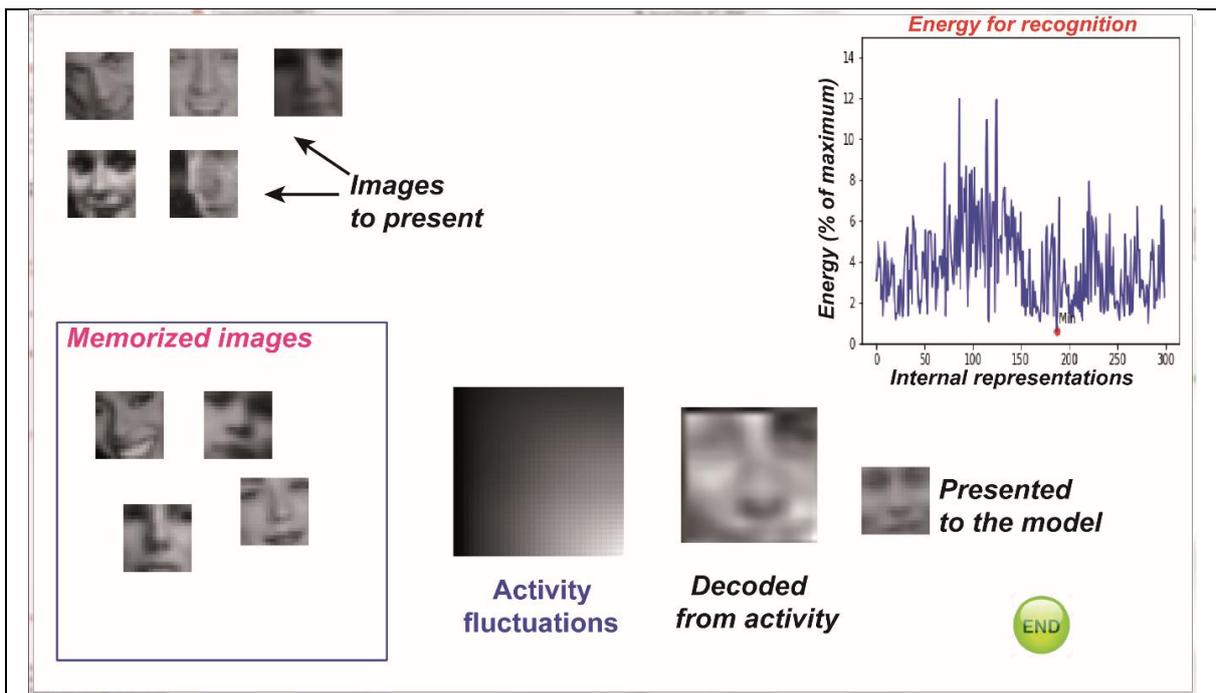


Figure 2. The integrative neuroenergetic model.

This is a commented screenshot of the model, which is better seen as a video in Supplementary materials or on the internet (<https://www.youtube.com/watch?v=kW9BzPiKEwQ>). A set of images is presented one by one to the fluctuating activity of the model, which comprises 300 internal representations of face patterns. The internal representation, which has the smallest difference with the representation of the input, is decoded by

spatial differentiation from the model activity. For each presented face, a graph indicates its energy difference with face patterns in the activity fluctuations (percent of the maximum energy level in the fluctuations). Thus, the minimum (red point) in the graph represents the face pattern most resembling the presented face. With each presentation of a face, the corresponding pattern in the fluctuations of the model becomes closer to the pattern imposed by the presenting face leading to the lower minimum in the graph. When the minimum is at zero, the face is memorized and is exactly reproduced the next time it is presented. The decoded face here represents the activity, which is slightly modified during the first presentations.

Firstly, we included the above-described energetic feedback, which rescales the levels of activity in the network if at some point of information integration the required amount of energy is not supported by the physiological mechanisms. One can predict that this rescaling does not influence the possibility of decoding the stimulation by differentiating the activity pattern. The modelled feedback mechanism illustrates that information coding may be independent of the level of energy per se but dependent on the differences of energy between the points (although of course some physiological limitations can exist for this principle as well).

In line with the free energy minimization principle (Friston and Stephan, 2007), we believe that spontaneous activity serves to maintain the representations of the expected stimulation based on previous experience. From the physical standpoint, free energy reflects a difference between internal energy and entropy at given temperature. It follows that minimizing free energy can mean not only minimizing internal energy but also maximizing

entropy. Entropy in this case reflects the number of possible states of internal representations, which code a variability in the external world – for example, a variability of faces, of car sounds etc. Thus, this variability is not just a disorder but has adaptive significance. The variability is coded by temporal fluctuations of the presented model, which includes the integrative activity patterns for 300 face patterns from the MIT face database (Rowley et al., 1998). A number of other face patterns from the MIT face database are taken as input to the model.

3. *Results and Discussion*

3.1 *Pattern recognition and predictive coding*

The input to the model tries to modify the fluctuations of activity (Figure 2) according to the above discussed neuroenergetic principles. Among all activity patterns in the fluctuations the easiest to modify is the pattern which has the closest energy levels to the activity imposed by the input. The graph

in the model interface reflects deviations of different patterns of activity from the activity imposed by the input. The red point on the curve indicates the pattern with the minimal deviation. Differentiation of this pattern reveals that it codes the most similar input from those coded in the fluctuations.

With each consecutive presentation of the new input, it modifies the initial activity pattern so that finally by differentiating it we obtain the image of the input memorized in activity fluctuations. The next time this input is presented, the minimum on the graph of energy quickly indicates the corresponding activity pattern. Thus, the model illustrates the adaptive significance of energy minimization. It was shown by electrophysiological measures that the minimal delay for image processing in the brain cortex is 40-60 ms (Bacon-Macé et al., 2005). According to the model presented here, this time should correspond to the choice of the closest pattern of integrative activity among those in the fluctuations and to the attempts to modify it. The video, which demonstrates the model can be accessed in Supplementary materials; the description is provided in Figure 2.

The highest rate of fluctuations can be maintained by electrical synapses, which are ubiquitous in the brain cortex and they are closely coupled with chemical synapses often in the same synaptic cleft (see (Pereda, 2014) for review). Fluctuations may partly be maintained by the bidirectional conductivity in electrical synapses. Along with synaptic

transmission, another potentially important factor which can influence rapid activity fluctuations is ephaptic coupling (Anastassiou et al., 2011). Activity-dependent plasticity of electrical transmission has been shown to rely on interactions of electric synapses with nearby chemical synapses via activation of glutamate NMDA receptors (see (Haas et al., 2016) for review). In accordance with this, we suggested on the example of mismatch negativity that repetitive presentation of the same stimulus may cause NMDA-related long-term plasticity in the specialized network resulting in the decrease of energy needed to recognize this stimulus (Strelnikov, 2007).

In the case of the lack of sensory input, as in profound deafness, one can expect the diminished predictive activity in the sensory cortex. If afterwards the auditory input is restored (by cochlear implants), one can expect the reactivation of predictive coding in the auditory areas. We showed with PET the reactivation of the auditory areas in experienced cochlear implant users during the resting state (Strelnikov et al., 2010). This resting state activity corresponds to the increase in their auditory performance and thus reflects the decrease in prediction error. We believe that our resting-state study of the restored sensory loss demonstrates a direct link between the free-energy minimization understood as predictive error reduction and metabolic activity.

The influence of predictive coding on perception was confirmed in our other study, in which we demonstrated that the EEG response to the auditory “deviance” can be triggered by the corresponding visual cues in the absence of the actual auditory deviance (Strelnikov et al., 2013). In this study, using an oddball paradigm we presented video clips with even (without emphasis) phrases as the frequent stimuli and with one word visually emphasized by the speaker as the nonfrequent stimuli. In spite of the same sound across standards and deviants, we detected a significant negativity after the start of the emphasizing facial movements. This negativity was confirmed by the statistical comparisons of the audiovisual and the visual (silent video) stimulations. Thus, in the appropriate context, the visual modality activates predictive coding for the auditory stimulation. Besides, behaviourally, all the subjects reported the auditory emphasis, which was actually absent in the auditory stimulation. This illusion was based on the visual prediction, which was not rejected by the brain during the auditory stimulation even though the real auditory stimulation remained unchanged. On the basis of our model, one can say that visual stimulation activated the corresponding pattern within the fluctuations of the auditory activity.

3.2 Internal representations of physical laws

In this article, we have a tacit hypothesis that the field of brain energy is characterized in terms of space and

time. We suggested that temporally changing spatial relations between points in the brain energy field can code perceived objects and showed by neural modelling that spatially integrative coding may correspond to such representations (Strelnikov, 2014; Strelnikov & Barone, 2012). There is a long-standing physical and philosophical debate whether space and time are real entities or products of our mind. This debate is also complicated by the impossibility to define such basic concepts in terms of any other less basic concepts. Given no solid proofs to claim the physical reality of space and time, one can stick to the undoubted notion that they exist in our representations of the world and are intuitively clear from the subjective experience.

With this approach, it is clear that either space and time perception or face perception are inevitably engrained in the physical laws of our body. These laws seem subjective when perceived from the interoceptive point of view. However, they reflect the same physical laws as in the rest of the universe. Our internal state has the same objectivity as any other event in nature and it needs to be studied to discover the physical laws behind it. Even if we imagine a fantastic object, this imagination is just another phenomenon of nature resulting from objective physical laws in the brain. This concerns any observation in nature, including our thoughts and internal representations. We believe that the physical approach, which objectivizes brain events, is

important especially in light of the brain energy field consideration.

If we say that the laws of energy transformation in our brain create internal representations, there is an inevitable question how these representations (e.g., mental images) are observed in our mind. The observing mechanism may be in some structures of the brain or in electromagnetic fields or in some other physical phenomena. Such a question corresponds to the question on the mechanism of consciousness and is outside the scope of this article. It seems rather probable that consciousness is a phenomenon related to electromagnetic fields, though there are considerable differences between the theories based on this assumption (see (Jones, 2013) for review).

3.3 Energy field and generalized forces

The average level of energy in a point of our model indicates the level of interaction or the potential for the interaction between different structures in this point (which is in reality not a point but a small volume like a voxel). If in one point interactions are higher than in the adjacent one, one can expect a force pushing in the direction from the point with a higher level of interactions to the point of the weaker level of interactions. This can be intuitively understood by the picture of air moving from spatial points with high pressure to points with lower pressure.

The direction of the highest spatial increase in the vicinity of a point and the value of this increase are

mathematically described by the gradient vector. Thus, at each moment of time one can predict the direction and magnitude of the force in each point on the basis of the known energy field. Using this transformation, one can obtain a vector of force in each point from the energy field where we have the level of energy in each point. This transformation is a common practice in physics; for example, the force of the electric field per point is obtained by calculating the gradient of the potential energy (the electric potential). Thus, the representation of the brain activity as energy field can be transformed to the field of generalized forces with a vector per point or per voxel. Evidently, these forces participate in establishing activity propagation in the brain and the above-discussed energy flows at each moment of time.

However, such a consideration would be true only for the instantaneous representations of brain energy fields because with time and in the absence of energy input to the system gradients tend to disappear. For instance, gradients of temperature between different points of the air in a room disappear with time in the absence of heaters. If we observe stable gradients in time-averaged brain images, it indicates that there are some forces which maintain the gradients (see (Strelnikov and Barone, 2012) for a more detailed discussion).

Once we know the spatial distribution of generalized forces at rest and during stimulation, we can deduce

another property – a sensory transforming field, which in each voxel transforms the direction and magnitude of force vectors. We have demonstrated that sensory input can be represented as a tensor field which transforms brain activity (Strelnikov, 2013). The peculiarity of this point of view is that it considers the influence of sensory input not per voxel but as acting on the differences between the adjacent voxels. Moreover, the transforming nature of sensory input can be observed at any level starting from sensory receptors' molecules, which change their shape so that interaction between their parts changes. The minimization of work and free energy are reflected in the transforming tensor field. Minimization of transformation from this point of view means trying to preserve the spatial structure of activity (i.e., the structure of the energy field) existing in the resting state.

3.4 Limitations and perspectives

The proposed model is based on the coupling between information increase and energy increase; this is a solid physical principle, which cannot be reconsidered by any future development of neuroscience. The limitations of the model, which also constitute perspectives for its development, are mostly related to its spatial organization. Though the activity patterns present a regular two-dimensional shape, which is easily decoded by spatial differentiation, the neural model behind consists of two neural populations with several layers each.

Intuitively, elements with similar functions should be rather close in space. The most effective is the network with the smallest size: two times increase of the size can cause even three times decrease of the information-energetic efficiency (Paprocki and Szczepanski, 2013). However, other factors can influence, for example, parts of the visual systems are separated by rather long distances. Thus, the link between the spatial organization of neural structures and the resulting energy field is not straightforward and requires further exploration.

Besides, energy fields can exist at different levels of processing. The holistic perception of a face, for example, which distinguishes it from other objects, may precede the featural exploration (see (Nakabayashi and Liu, 2014) for review). In our model, the mathematically simple integration method is chosen, which corresponds to the rows and columns of the flat two-dimensional input. In a real situation, the input has complex non-rectangular shapes and the integration mechanism can follow other strategies. The integration can start not in the corner but from the most meaningful parts of the image, like eyes and mouth for the face. The biological ways of information integration coupled with energy increase constitute a direction for further neuroenergetic research.

Moreover, as often happens in physics, insights obtained from the reformulation of a problem in terms of energy and energy transformations can advance

our understanding of situations where energy does not figure as a variable of interest. In particular, reasoning in terms of energy can render the description of a process simpler. By analogy, to study air flows in a room, one can start measuring the trajectory of each molecule of the air, and this is a completely reasonable approach. However, it is much simpler to obtain values of temperature (reflecting average kinetic energy of molecules) in different points of the room to determine air flows. As discussed above, an energy-based understanding of feedback provides a simple explanation compared to any other attempt to understand the necessity of this mechanism. Energy-based descriptions of activity patterns are also much simpler than those based on the rates of spikes, for instance. As any kind of brain mechanism can be reformulated in energy terms, the energy field approach potentially represents a link between different approaches to brain function starting from molecular up to cognitive levels.

4. Conclusions

The energy field approach does not contradict any other approach in neuroscience but presents a general and abstract way to deal with different levels of brain functioning. Elements of the energy field can represent voxels as in

neuroimaging, particular neuroglial populations, neurons and even molecular structures. The advantage of the energy field approach is that energy characterizes any type of interaction at any chosen level. Depending on particular needs, the values per element of energy fields can be free energy, electromagnetic energy, heat etc. This opens the possibility of comparing different types of interactions by comparing energy fields with different types of energy per element of the field. Recalculating any neural model in terms of energy levels, one obtains a tool to link this model to the molecular machinery of the brain (glucose, ATP, ATPases, oxygen etc.). Ideally, if one knows an energy level per point in the brain, one knows sufficiently enough to predict brain function.

Acknowledgements

We thank Amirouche Sadoun for the reading and comments.

Competing interests statement

There are no known competing interests.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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