BRAIN RESTING STATE, LANDAUER PRINCIPLE AND CARNOT CYCLE

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Abstract

The brain displays a low-frequency ground energy conformation, called the resting state, which is characterized by energy/information balance via self-regulatory mechanisms. Despite the high-frequency evoked activity accumulates information from the detail-oriented sensory processing of environmental data, nevertheless the brain's automatic regulation is always able to recover the resting state. Indeed, we show that the two energetic processes are complementary and symmetric: while activation decreases temporal dimensionality via transient bifurcations, the ensuing brain's response leads to procedures that satisfy the Landauer's principle. Landauer's principle, which states that information erasure requires energy, predicts heat accumulation in the system: this means that information accumulation is correlated with increases in temperature and with actions that recover the resting state. We explain how brain synaptic networks frame a closed system, similar to the Carnot cycle, where the information/energy cycle accumulates as energy of synaptic connections, and then dissipates in the resting state. In deep learning, representation of information might occur via the same mechanism.

Key words:
Energy/information exchange, information erasure, entropy, Landauer's principle, Carnot cycle, deep learning.

INTRODUCTION

The cortical brain is an evolutionary marvel which interacts with the outside world via self-regulation, based on its resting or ground state. The resting state, disturbed during stimulus and sensory processing, is recovered by automatic operations. In warm-blooded animals, the brain's energy is greatly increased: although the human brain represents only 2% of the body weight, it receives 15% of the cardiac output, 20% of total body oxygen consumption and 25% of total body glucose utilization (Clark and Sokoloff, 1999). It is thought that the baseline brain energy consumption has been almost exclusively dedicated to neuronal signaling (Shulman et al., 2009). This almost constant and huge energy use maintains the brain's alertness, even during sleep, by an active balance between inhibitory and excitatory neurons (Dehghani et al., 2016; Okun and Lampl, 2009). The slightest variations in excitation determine whether a spike is generated. Such a delicate balance of excitatory and inhibitory neurons turns the resting state into a highly energy-requiring state (Gruenert et al, 2011; Kim and Fiorillo, 2017; Vanag et al, 2011). Even in the absence of stimulus, the equilibrium of excitatory and inhibitory neurons produces seemingly arbitrary bursts of resting state's activation (Luczak et al., 2015). This active balance between contrasting influences ensures the brain's ability for rapid, targeted response to environmental stimuli. For example, changes in inhibitory neurons increase brain frequencies and their energetic needs (Gruenert et al, 2011). Via the sensory system, the brain partakes in the energy/information exchange with the environment: the precarious energy balance turns interactions into a closed physical process: the thermodynamic entropy.

Entropy is a concept rooted in experience and experimental data. Different scientific fields (such as information theory or quantum mechanics) have their own, although related, definitions (Duncan & Semura, 2004; Martin et al., 2013), with a significant amount of disagreement over diverse definitions of information and entropy. To make just a few examples, it has been recently suggested that the negative work cost of erasure stands for negative entropy (del Rio et al., 2011); furthermore, entropy might drive order-increasing interactions, in closed systems under special circumstances (Haji-Akbari et al., 2009; Haji-Akbari et al., 2011; Bertalanffy, 1933).

The brain's resting state allows stimuli-related energy changes, based on the laws of thermodynamics. Sensory activation is coupled to information increase via enhanced frequencies (Yamada and Kawabe, 2011), so that the brain's energy/information cycle might form a closed, thermodynamic system, similar to the Carnot cycle. To gain better insight into the nature of entropy, here we investigate the role of stimulus during the entropic changes occurring during cognitive process.

Landauer's principle (i.e., the erasure of information produces a minimal quantity of heat, proportional to the thermal energy) (Landauer, 1961), shows that a certain amount of work is necessary to erase a bit of information, dissipated as heat to the environment. The needed amount of work couples with the function of uncertainty about the system, because information about the system reduces the cost of erasure. Likewise, in the brain, the information value of stimuli, which determines the extent of response, is highly subjective. For example, the correlation of neuronal activation with visual stimulus is mediated by intracortical mechanisms (Doiron et al, 2016). Furthermore, the oscillation dynamics of local neurons reflect the anatomical/functional occurrence of intra-cortical feedback, thalamocortical networks, global signal propagation, synaptic clustering, network states and other residual activities well beyond the sensory value of inputs (Wright et al., 2016). Thus, the connection between 'information' and 'work' is the function of environmental entropy. Thus, applying Landauer's principle to the brain's cognitive process might uncover the thermodynamic nature of the energy/information exchange during the sensory process.

One of the biggest puzzles in neuroscience is how comprehension and meaning emerge from the complex patterns of neural activity. Hemodynamic, metabolic parameters, membrane potential, electric spikes, neurotransmitter release have been studied (Gazzaniga, 2009; Kavalali et al. 2011; O'Donnell and Van Rossum 2014). EEG, lesion studies (Buzsaki and Watson, 2012; Jensen et al., 2014), diffuse tensor imaging, MEG and fMRI analysis (Friston, 2010; Sporns, 2013; Tozzi, 2015) demonstrate that consciousness results from coherent, globally coordinated electric activities (Koch et al., 2016; Touboul, 2012). Since electric activities in the brain is correlated with conscious actions, the mind forms a unified experience by connecting sensory perception with mental states based on event related potentials (Guterstam et al., 2015; Mancini et al., 2011). An ensemble of cortical and subcortical regions (including the rostral anterior cingulate, precuneus, posterior cingulate cortex, posterior parietal cortex, dorsal prefrontal cortex, along with the caudate head, anterior claustrum and posterior thalamus) supports the occurrence and convergence of multiple resting-state networks (Bell and Shine 2015). Resting-state network convergence might facilitate global brain communication and underpinning systems-level integration in the human brain (Northoff et al., 2010). Local electromagnetic potential differences in the complex neural landscape vary according to the principle of least action, forming metastable changes of spatiotemporal patterns that are isomorphic with cognitive and phenomenal occurrences (Fingelkurts et al., 2009; 2013). Via recurring, highly reproducible harmonic functions (Atasoy et al., 2016) the brain's resting state has been shown to form the functional curvature of a four dimensional torus, which manifests itself as repetitive patterns of mental trajectories (Tozzi and Peters, 2016a,b; Tozzi et al., 2016). Even in the absence of synaptic anatomical connectivity, the resting state displays great autonomy and complexity, indicating its essential role as the ground state of the brain (Robinson et al., 2016).

Biological organisms live with a temporal expiration date, determined by the access to air, water, food, mating, which modulates behavior between urgency and relaxation. The inner clock of brain activity is not connected to any local system, but results from a global temporal rhythm (Teki, 2016), which originate in midbrain dopamine neurons (Soares et al., 2016). For example, sleep compresses the daytime firings of neurons in time (Watson & Buzsáki, 2015). In fact, time turns into a relative experience, because intentional binding formulates the perception of time (Jo et al., 2014) and gives rise to agency. The importance of temporal considerations is further illustrated by the connection between deviations in time perceptions and brain diseases (Kranick & Hallett, 2013). Major depression seems to slow time perception (Stanghellini et al., 2016), whereas time passes at a jerky in schizophrenia. ~~Ticks and~~ Parkinson's disease is characterized by both impairment in time control as well as time delay. Therefore, time perception, an elementary part of the formation of conscious experience, might be regulated by the energy/information cycle of the brain. Understanding the brain's energy/information exchange is critical, because disturbances in this cycle can cause health problems and disease without any obvious pathologic change in brain morphology.

The gradually improving responses to stimuli have molded brain organization into a coherent, structural, organizational mirror of physical systems (Déli, 2015). However, biological survival needs, such as water, food, reproduction, etc. to be dictated by a relativity of time and an oscillating motivation between urgency and relaxation. Mental operations, which form an increasingly improving mirror of the social environment, constantly respond to the environment and modify it, forming their common evolution. This way, environmental abstraction becomes integral part of a wholesome mental world, engendering an interconnected system which determines and governs thoughts, intentions and behavior according to the laws of physics.

Discussion

Theoretical foundations

Stimuli provide information input that leads to a thermodynamic relationship with the environment, in the form of the electric activities of the neuronal network. Because all evoked oscillations are greater than electric activities of the resting state and accompanied by entropic and dimensionality changes, the brain's information/energy cycle between stimulus and recovery of the resting state can be analyzed based on thermodynamics. Stimulus generates heat that can be assessed in terms of enhanced brain frequencies, synaptic modification. That way, the brain's responses to stimulus in the present state shapes its ability for future interactions. The energy devoted to neuronal connections satisfies the Landauer's principle, which reflects sensory interaction based on energy/information exchange. Evoked states are information-saturated, thus produce high entropy and involve high frequencies; these high frequencies are unstable and, due to their huge energy requirement, become energetically untenable over time.

Because the sensory system transforms spatial information into the temporal language of the brain oscillations, the brain is organized along temporal coordinates (Buzsaki et al, 2013, Fingelkurts & Fingelkurts, 2014). Here we analyze the brain's global energy/information cycle in terms of entropic and topological considerations, in view of the correlation between physiology and electric activities. We achieve generalizations that allow the assessment of the relationship of the brain's electric activities--independent of their scale, magnitude, specific features and local boundaries—and cognitive experiences. We show that interconnected synaptic networks form a closed system, which leads to self-regulation based on energy/information transformations satisfying the Landauer's principle. Information accumulation corresponds to an increase in temperature indicated by enhanced frequencies, so that erasing information frees energy, which increases order through the energy accumulated in cortical synaptic connections. Therefore, self-regulation of brain activities is based on low entropy.

Brain activities do not exist in isolation; rather from a self-regulating, interconnected and coherent energy system. Moreover, brain models suggest that constantly changing nervous activities take place on different kinds of curvatures of the brain phase space (see, for example, Sengupta et al., 2016). Thus, brain activity can be assessed based on topological activity. Topology suggests structures such as a toroidal view of brain activities and the projection of percepts to higher dimensional spaces (Tozzi and Peters, 2016a) as well as mappings of antipodal points on opposite perceived images into hyperbolic manifolds (Peters, 2016a). Because disturbances in this self-regulating physical network might play a role in various pathologic conditions, we will take into account the relationship between temporal dimensionality and entropy, and the brain's evoked energy/information exchange (interaction).

Relationship to the Carnot cycle

The Carnot cycle provides an upper limit on the efficiency that any classical thermodynamic engine can achieve during the conversion of heat into work. No engine operating between two heat reservoirs can be more efficient than the corresponding Carnot engine. The Carnot cycle is an idealization, since no classical engine is reversible and physical processes involve some increase in entropy. Surprisingly, the Carnot bound can be surpassed in microscopic systems, because thermal fluctuations induce transient decreases of entropy, allowing for possible violations of the Carnot limit. Such a miniaturized Carnot engine was realized using a single Brownian particle (Martinez et al., 2016). The Carnot

cycle represents execution of work in a heat bath. The process consists of two isothermal processes, where the working substance is respectively in contact with thermal baths at different temperatures T_h and T_c, connected by two adiabatic processes, where the substance is isolated and heat is neither delivered, nor absorbed (Shangi et al., 2014).
In the brain, neural activation is forwarded via synaptic connections, allowing the analysis of energy/ information exchange based on the principle of least action. We suggest that the nervous entropic changes in information and resting state display a thermodynamic relationship with the Carnot cycle. The cortical insulation of the limbic system, which lies on the top of the resting state, correlates with the occurrence of evoked potential. In turn, evoked potential triggers electric activities that restore the resting state (Figure 1). This recurrent energy /information exchange forms a closed system and allows the examination of brain activity based on thermodynamic considerations. Landauer's principle shows how heat production is tied to information/energy transformations. The frequencies of the brain's evoked cycle reflect both its computational limit and the added heat of stimulus, which also determines the energy usage via synaptic changes.

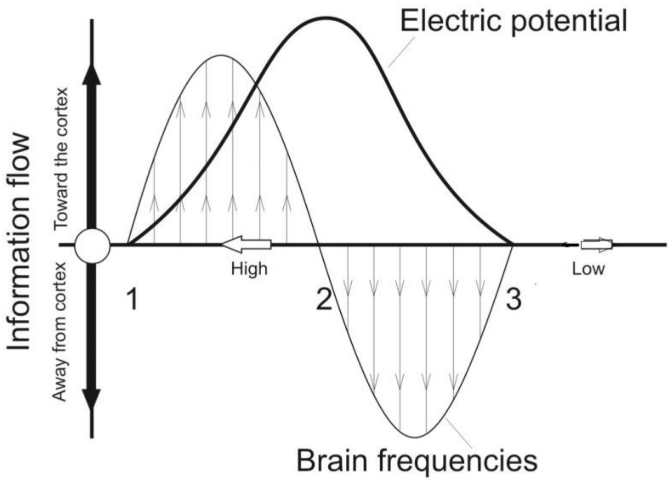

Figure 1. Changes in energy balance due to stimulus. The brain frequencies change from high, on the left (#1), to low, toward the right (#3), determining the direction of information flow in the brain (shown by thin line). The resting state of the brain is energy neutral before stimulus (#1) and after a response (#3). Evoked potential are illustrated by 2. The high energy need of enhanced brain frequencies induces an urgency (indicated by 1), whereas the high amplitude of the lowest frequencies permits an overarching, global connectome and mental vision, indicated by 3.

The brain's energy/information cycle:

In the brain, stimuli increase frequencies, which correlate with heat absorbed by the system, giving rise to an increase in temperature (Figure 2). This phase, marked DA in the picture, correspond to the Carnot cycle's adiabatic compression phase. In a classical gas, heat production is function of particles collisions, which is dependent on the temperature and the number of particles (volume of the gas). In neural networks as well as in deep learning systems, network connections, which spread information, correlate with collisions. Therefore, number of dimensions corresponds to the volume of the gas, whereas the depth of the network might represent the temperature of the system. The second phase, marked by AB, in which the frequencies spread throughout the whole cortex, stands for the isothermal expansion (the signal expands, exerting work). The third, relaxation phase, marked by BC, stands in the brain for evoked potentials reversing the direction of the electric flow on lower frequencies; the reduction of temperature exerts work, by accumulating energy as the complexity of synaptic connections. In this phase, meanings and concepts might emerge, based on the subjective information value of the stimulus. The fourth phase, marked by CD, correlates with the contraction phase of the cycle: the brain's electric activities contract and recover the resting state.

The amount of thermal energy transferred in the process is the following:

$Q = \int_A^B TdS$ (1)

The area inside the cycle will then be the amount of work done by the system over the cycle.

W= $\oint PdV = \oint(dQ - dU) = \oint(TdS - dU) = \oint TdS - \oint dU = \oint TdS$

Since dU is an exact differential, its integral over any closed loop is zero: it follows that the area inside the loop on a T-S diagram is equal to the total work performed
The amount of energy transferred as work is

W= $\boldsymbol{\oint PdV = \oint TdS = (T_H - T_c)(S_B - S_C)}$
The total amount of thermal energy transferred from the hot reservoir to the system will be

$$Q_H = T_H(S_B - S_A)$$

The efficiency η is defined to be:
η= $\frac{W}{Q_H} = 1 - \frac{T_C}{T_H}$

where

W is the work done by the system (energy exiting the system as work),
Q_C is the heat taken from the system (heat energy leaving the system),
Q_H is the heat put into the system (heat energy entering the system),

T_C is the absolute temperature of the cold reservoir, and

T_H is the absolute temperature of the hot reservoir.
S_B is the maximum system entropy
S_A is the minimum system entropy

The heat absorbed by the system toward order increasing transformation:

dQ = T dS
Therefore, the amount of released heat corresponds to the entropy decrease (increasing synaptic complexity) of the system.

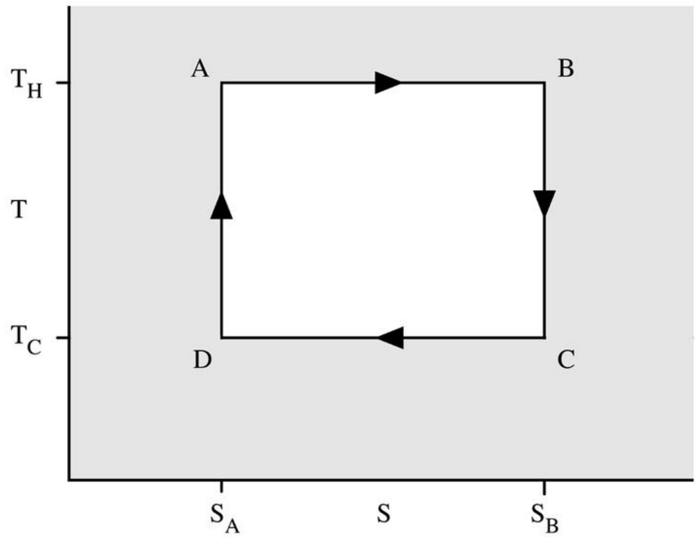

Figure 2: A Carnot cycle acting as a heat engine, illustrated on a temperature-entropy diagram. The cycle takes place between a hot reservoir at temperature TH and a cold reservoir at temperature TC. The vertical axis displays the temperature, whereas the horizontal axis the entropy. In the brain, during the (DA)compression phase, the stimulus increases the frequencies,due to heat absorbed by the system. In neural networks as well as in deep learning systems the depth and number of connections of the network is related to the system's ability to produce work or to learning.(AB):the frequencies spread throughout the whole cortex: the signal expands, exerting work. (BC): evoked potentials reverse the direction of the electric flow on lower frequencies (the temperature decreases, the energy leaves the system). CD: the electric activities contract and return to the resting state.

The brain's energy/information cycle determines the temporal dimensionality of electric activities in understanding, comprehension and learning

Landauer's principle, originally developed for computation, was proven in increasingly sophisticated experiments and consequently, applicable for the tightly regulated environment of the brain (Bérut et al 2012; Hong et al., 2016; Landauer, 1961). According to the principle, information accumulation by electric activities of the brain during evoked states corresponds to enhanced temperature. Landauer's principle also shows that the recovery of the resting state frees energy for work, due to information/energy transformation. This process correlates with lower temperature. Decreasing frequencies form a sink of low information content and increasing degrees of freedom (Tozzi et al, 2017). Thus, evoked activities modify the temporal field curvature and dimensionality via bifurcations in the brain's electric activities, whereas the resting, equilibrium state formulate Euclidean torus (Tozzi and Peters, 2016a). In contrast, decreasing frequencies increase the oscillations amplitude (da Silva et al 2016), thus activating greater brain regions, or modules. Simultaneous activation of wider regions of the brain might engender mental coherence, ideas and learning. The potential assessment of neuronal activations and global cognitive processes in terms of brain energy cycle has immense potential in understanding various neural conditions, such as depression, PTSD and other neural diseases.

Relationship between the resting state and learning

Sensory interaction increases information content and entropy, but the living brain incessantly recovers its resting, low entropy state. Maintaining and restoring the resting state seems to be an inherent and essential part of healthy brain operation. Spontaneous brain activity, accounts for up to 70% of the great energy need of the brain (Tomasi et al., 2013). Information input enhances frequencies and compresses time (by forming positive temporal curvature), which increases entropy, similar to a Brownian motion. In accordance with Landauer's principle, heat must be released when the resting state is restored (Pop-Jordanova and Pop-Jordanov, 2005). Surprisingly, deep learning can also be divided into phases that constitute similar entropic effects and energetic transformations, consisting of compression of information and relaxation, which culminates in representation of information (Shwartz-Ziv and Tishby, 2017; Gao & Duan, 2017). This entropy conservation in closed systems is expressed by the low entropy principle (Déli, 2017).

Entropic considerations of the brain's topology and activities: a mathematical treatment

Brain activities might follow particle paths traversing surfaces of geometric spaces formed by temporal rhythms of electric activities (Tozzi and Peters, 2017). Thus, electric activities might manifest as dimensional structures, that change from n-dimensional (e.g., a two-dimensional disk), to n+1 -dimensional structure (e.g., negative curvature surface, which correspond to temporal expansion) and n-1 dimensional surface (positive temporal curvature surface, which correspond to temporal compression).Since the energy cost of sensory processing is proportional to frequencies, sensory information is translated into an energy signal in the brain. The sensory transmission toward the sensory cortex via fast oscillations, together with response via slow oscillations, form the polarity effects of the brain's electromagnetic flows. Nevertheless, the strength and extent of synaptic connections (i.e. increasing synaptic complexity) differ before and after stimulus (Figure 3). The enhanced neural organization must be proportional with the release of thermal energy and consequent reduction of entropy. Therefore, stimulus, which increases temperature, might supply the energy to modulate synaptic strength or form new connections in the brain. The organizational constancy and charge neutrality of the resting state guarantees that the energy difference due to the released heat (as in a heat engine) leads to a higher order of the synaptic organization. Therefore, the brain is an active member of the environmental energy cycle.

A topological view of this synergy between the brain and the environmental energy cycles exhibits strong proximity both spatially and descriptively. The spatial strong proximity (Peters, 2016a) of the brain and environment is in the form of temporally overlapping cerebral energy and environmental energy readings (*e.g.*, the occurrence energy highs and lows of the one set of readings overlaps with the occurrence similar readings of highs and lows in the other during the same timeframe). For example, let *A* and *B* represent nonempty sets of recordings of brain and environmental energy recordings that are temporally concomitant *in situ*. The spatial form of strong proximity is denoted by $\overset{w}{\delta}$. From the strong proximity axiom (Peters, 2016b, p. 16), we have

$$A \overset{w}{\delta} B \text{ implies } A \cap B \neq \emptyset,$$

i.e., the two sets of energy readings overlap. There is also a descriptively strong proximity between the two sets of energy readings. The descriptive form of strong proximity is denoted by $\overset{w}{\delta}_{\vartheta}$. The subscript ϑ refers to a mapping $\vartheta : A \to \mathbb{R}^n$ on the set of readings *A* into an *n*-dimensional feature space $\mathbb{R}^n$, defined by $\vartheta(x)$ (a feature vector in $\mathbb{R}^n$,) that is a feature value of a reading $x \in A$. Similarly, there is a mapping $\vartheta : B \to \mathbb{R}^n$ on the readings in *B* into the feature space $\mathbb{R}^n$. The two sets of energy readings with common descriptions give rise to a descriptive intersection (denoted by $\underset{\vartheta}{\cap}$) of the two sets:

$$A \underset{\vartheta}{\cap} B = \{x \in A \cup B : \vartheta(x) \in \vartheta(A) \,\&\, \vartheta(x) \in \vartheta(B)\},$$

i.e., there is at least one cortical energy reading (e.g., cortical energy amplitude) in *A* that has the same description as an environmental energy reading (e.g., environmental energy amplitude) in *B*. From these structures, we can elicit a strong descriptive proximity between *A* and *B* (Peters, 2016b, p. 28-29) in terms of

$$A \cap B \neq \emptyset \text{ implies } A \underset{\vartheta}{\cap} B \neq \emptyset,$$

i.e., overlapping energy readings implies an overlap between the descriptions of the two sets of readings. This observation leads to the following descriptive proximity property:

$$A \overset{w}{\delta}_{\vartheta} B \text{ implies } A \underset{\vartheta}{\cap} B \neq \emptyset.$$

The importance of this pair of proximities lies in the fact it is then possible to derive Leader uniform topologies on pairs of sets of energy readings. This is done in the following manner. Start with a collection of sets of cerebral energy readings $\bigcup A_i$ and a collection environmental energy readings $\bigcup B_i$ gathered during withing the same timeframe. For each given subset $A \in \bigcup A_i$, find all $\mathrm{B} \in \bigcup B_i$, such that $\mathrm{A} \overset{w}{\delta_\vartheta} \mathrm{B}$. Doing this for each given set of cerebral energy readings, leads to a collection of clusters of strongly near sets of readings. In effect, we have topologized the collections of energy readings by introducing a Leader uniform topology (Leader, 1959; Peters, 2015) on the space of energy readings.

An important outcome of topologized energy readings is the introduction of a search space in which clusters of readings exhibit spatial and descriptive proximities.

Moreover, our approach shows the role of observer in information processing: the history and current state of the brain is just as important in determining the degree of neuronal activation as the stimulus itself. Thus, the state of the observer i.e. the brain, determines the information value of the stimulus. This way, information processing in the brain is holographic. Thus, the degree of comprehension or understanding (manifested as increasing synaptic complexity) has a large subjective quality, the observer effect.

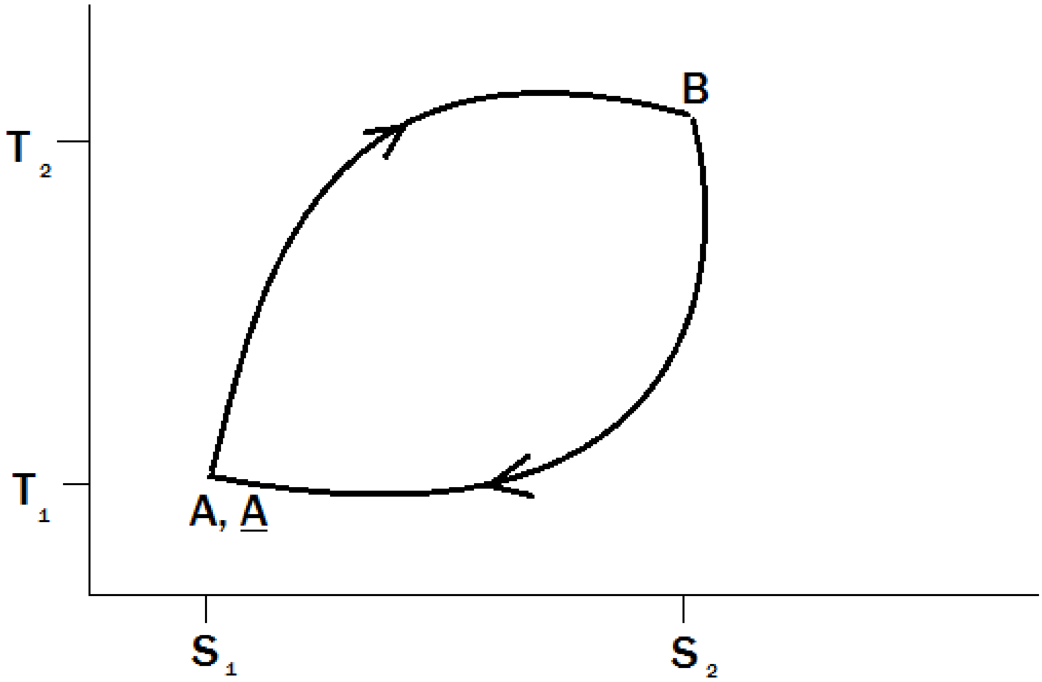

Figure 3. The entropic changes during a learning cycle. (A) Sensory information activates the neural system by enhancing the frequency of oscillations, which corresponds to changes in temperature. The increase in frequencies leads to positive temporal curvature, which compresses time perception. The entropy also increases between S1 to S_2 . (B) The second part of the cycle recovers the low entropy state and the Euclidean geometry. The slowing frequencies correspond to negative temporal curvature and to increases in time perception, which slows down the system. (A) The entropy decrease leads to order, manifested as synaptic complexity, underpinning concepts and meaning. Therefore, the energy increase between A and A, is supplied by sensory stimulus. Or in other words, perception of stimulus modifies mental organization.

Conclusions

Physical principles often find application in other, seemingly unrelated fields, proving that the physical laws underline all of nature. The brain's immense energy use engenders a readiness on which interaction with the environment is possible. Here, in our investigation of brain processes, we analyzed the resting state in light of two important physical principles, the Carnot cycle and Landauer's principle. We traced back the brain electromagnetic activities onto these principles based on the principle of least action.

The brain's fundamental regulation is founded on field effects of the resting state; in its constant interaction with the environment, the mind constantly changes and adapts. However, the maintenance of the resting state against the constant barrage of sensory activation by the environment contributes to the brain's immense energy consumption. Sensory activation corresponds to information/entropy increase and the reduction of temporal dimensionality (Tozzi and Peters, 2016a). Landauer's principle in the brain means that evoked activities correspond to enhanced 'temperature,' whereas recovery of the resting state correlates with cooling down (Pop-Jordanova and Pop-Jordanov, 2005) and the initial and final conditions differ in neural organization. The incurred thermal energy might enhance neural organization, which engenders meaning, mental coherence and correlates with low entropy. Therefore, stimulus, which generates activation, might supply the energy to modulate synaptic strength or form new connections in the brain. Thus, Landauer's principle might explain the relationship between the electric activities of the brain and the physiological states of the mind. Two sides of the brain energy/information cycle are bound by the organizational constancy and charge neutrality of the resting state. The brain as well as deep learning systems maintain a permanent readiness state, on which energy/information cycle with the environment can take shape. Therefore, both in the brain and in deep learning systems, Maxwell's demon can reverse the second law of thermodynamics. The existence of the stable resting state turns the brain into a globally static system. In this way, the brain's self-regulation utilizes the information input delivered by the environment, leading to an increase of its neural organization (mental capacity, corresponding to greater synaptic complexity). Thus, the brain is part of the thermodynamic cycle of the environment. In a highly interconnected relationship, the brain modifies its environment, but stimulus also evolves and changes the brain. A connection between life processes and the entropic changes of the environment was suggested by Schrodinger (1945) and was further developed by Déli (2015). We have shown that the constant barrage of information by the environment induces a thermodynamic cycle in the brain, similar to the Carnot cycle, which increases synaptic organization and complexity, *i.e*. order. The ability to transform information into energy seems to be the most essential quality of the brain. However, the brain is compelled by comprehension and interpretation of visual, auditory, tactile experience or taste by the stimulus. The brain does not engage the environment. Instead, the environment highjacks the brain, by forcing it to process incoming information (Déli, 2015; Déli et al., 2017). Furthermore, the environment charges the brain with sensory information: instead of the brain having control over the environment, the environment provokes and extorts the brain's energy consumption needs. Feeding on complex organic compounds reduces the environment's entropy. Thus, evolution of life is the environment's convenient way to reduce entropy. The brain's immense energy use during its resting state ensures that very tiny changes in potential can trigger considerable activation and order increasing transformations. Thereby, thinking, memory and other conscious processes require minute computational costs. This permits us to uncover how energy/information transformations in the brain satisfy physical principles.

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