

Study of Human Perception of Time using Brain Entropy and Inverse Problem Analysis of Brain Activities



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Abstract

We discuss here human perception of time in the context of brain entropy. Works by brain physiologists and time philosophers are briefly discussed here as a centerpiece of the study. Assuming that entropy is one of the significant elements of the problem, we wanted to explore its thermo-dynamical and information-theoretical representations. Are the physical and informational aspects of reality related to humans' temporal perception? The significance of the notion of negentropy and Brain entropy shall be assumed and scrutinized. As a matter of practical significance and human personal curiosity, we attempt to shed some light on the persistent question: why is the human perception of time changing with passage of an individual's life? Where does time go? Is it about our perception of time, or is the time itself a perception?

The attempt here is made to estimate the effect of the human age on the perception of time. The "elastic band model" is one of such hypotheses. The project introduced here aims at the study of the brain functions exposed by some experimental and analytical techniques. The previously obtained results have been published as preprints under the title "Inverse Problem's Solution Using Deep Learning: An EEG Based Study of Brain Activity". The focus of this project is on the subject of Brain Entropies and Time Perception by Humans. More specifically – here we are looking at a link between the state of the brain affected by aging and the individual's perception of time.

Keywords: Perception of Time; Brain Entropy; EEG; FMRI; Inverse problem; Neuron clusters; Method of Fundamental Solutions

Abbreviations: BEN: Brain Entropy; KS: Kolmogorov-Sinai

Introduction

Among other fundamental aspects of human consciousness, the time perception plays a very significant role in our everyday life and, more generally, presents itself as an element of cognition on the existential level. What is time as we perceive it? Are there factors that affect the perception and change it under some circumstances? Why, for example, does the human ageing make outside time perceived like flying while the state of elation or agitation makes time seemingly densely packed? In relation to the above questions, we discuss here human perception of time in the context of brain entropy. Works by brain physiologists and time philosophers briefly discussed here are pointing at different possible explanations of time phenomenon. Assuming that entropy is one of the significant elements of the problem, we shall explore its thermo-dynamical and information-theoretical representations. Are the physical and informational aspects of reality related to humans' temporal perception? The significance of the notion of brain entropy and its informational counterpart, the negentropy, shall be assumed and scrutinized. As a matter

of practical significance, we attempt to shed some light on the persistent question: why is the human perception of time changing with passage of an individual's life? Where does time go? On a more abstract level, the following question remains unanswered: Is it about our perception of time, or is the time itself a perception? Obviously, we are not in any position here to discuss fully this, very general and fundamental, question.

Instead, we are focusing here on the following aspects of the time perception. We consider the human perception of time as a cognitive response to the brain registered events. In the event driven model, time intervals are perceived using a past event as it was reflected and stored in the brain. To identify a time interval, the closest registered event should be found in the memory. The event's information, as assumed, can be located in different parts of the brain. The short-term memory is, commonly, associated with the brain's frontal lobe, while the long-term memory is in hippocampi. However, the latest research points at some evidence that mental categories should be considered as the whole-brain

neural activity and an assortment of behaviors at the same time. Functional categories such as memory, perception and attention can then be understood as “features of the whole brain state.” Thus, the assumption can be made that the state of irregularity of the overall brain activity characterizes the accessibility of the event related memory. This defines the perception of the time intervals separating the registered events.

We hypothesize that the perception of time can be assessed by a metric associated with the brain entropy.

The brain entropy characterizes the accessibility of stored past events. In the case of reduced brain alertness, the more distorted the status of the brain is the more likely the closest past event will not be found – the intervals between stored events will increase. Therefore, time will be internally perceived as slowed down when compared to the surrounding time perceiving entities. Such entities used as the bases for the time perception comparison can include not only the natural and man created devices but also the perception subjects such as other humans themselves. The project introduced here aims at the study of the brain functions exposed by the experimental and analytical techniques. The previously obtained results have been published as preprints under the title “Inverse Problem’s Solution Using Deep Learning: An EEG Based Study of Brain Activity” [1, 15]. The focus of this project is on the subject of Brain Entropies and Time Perception by Humans. More specifically – here we are looking at a link between the state of the brain affected by different aging and the individual’s perception of time.

Human Perception of Time – Brief Review of Scientific and Philosophical Pursuits

The metaphysics of time perception

We start with a couple of famous quotes that refer to examples of phenomena that forever surprise the human mind seeking the answer and explanation. The human perception of time is on the list of the most amusing subjects of mind. The fundamental aspects of time and its perception have been discussed in Stanford

Encyclopedia of Philosophy [3]. “We see colors, hear sounds, and feel textures. Some aspects of the world, it seems, are perceived through a particular sense. Others, like shape, are perceived through more than one sense. But what sense or senses do we use when perceiving time? It is certainly not associated with one particular sense. In fact, it seems odd to say that we see, hear or touch time passing. And indeed, even if all our senses were prevented from functioning for a while, we could still notice the passing of time through the changing pattern of our thought. Perhaps, then, we have a special faculty, distinct from the five senses, for detecting time. Or perhaps, as seems more likely, we notice time through perception of other things. But how?”

i. A. Einstein considered time as illusion:

“People like us who believe in physics know that the distinction between past, present, and future is only a stubbornly persistent illusion” [4].

ii. Abhijit Naskar, has noted:

“Time is basically an illusion created by the mind to aid in our sense of temporal presence in the vast ocean of space. Without the neurons to create a virtual perception of the past and the future based on all our experiences, there is no actual existence of the past and the future. All that there is, is the present” [5].

Time dilation

In general physics and the relativity theory, time dilation is the difference in the elapsed time as measured by two clocks. It is either due to a relative velocity between them or to a difference in gravitational potential between their locations. Time dilation, therefore, means that on one person’s watch time slows down while other humans may feel that much more time have passed. It is a common situation familiar to people of different ages (Figure 1). When asked – in the absence of any available time measuring devices - What time is it? we should start with, first, understanding how to answer the following question: What is time as we perceive it?



Figure 1: Two human brains register the readings on two clocks (the left and right ones) differently depending on the system they belong to.

Chemical Mechanism of Time Perception

It was a common belief that humans have no specific organs to measure time – so, what do we know about the mechanism related to time perception? The neurotransmitter dopamine plays a

critical role in how we perceive time. Dopamine has many different effects on how much time we think has elapsed in a given period, and these effects may conflict confusingly. Some studies have found that increasing dopamine speeds up an animal’s internal

clock, leading it to overestimate the passage of time; others have found that dopamine compresses events and makes them seem to be flying; still others have uncovered both effects, depending on context. We pursue here a hypothesis that time perception is affected by the brain entropy (BEN) following the analogy with the thermo-dynamical entropy as a measure of disturbance in the system.

The status of the brain characterized by the BEN affects, in its turn, the processes we identified as Event Driven Models.

Brain Entropy

The brief history of Entropy

Here, the reference to the title of the Steven Hawkins' seminal book, *The Brief History of Time*, is not just a simple allusion. Any discussion of time should include consideration of entropy as a natural measure of time: of all known physical properties, only entropy is the never decreasing metrics, like time.

a) Why entropy

There are various interpretations of entropy and different contexts where it is applied: physics, information theory, biology, even sociology, et cetera. There is, however, at least, one common property that makes all definitions and forms of the entropy share a common ground: that is the relation to the notion of chaos and uncertainty. Entropy is the measure of uncertainty. It reaches the maximum as uncertainty and disorder increases. When entropy is at its maximum and can't increase, no possible activities can be carried out. The chaos (disorder) is the end point of any development in isolated systems. This state is called "the thermo-dynamical death". The time's axis points to the state with the maximum entropy.

b) Information

In Theory of Information, the Shannon Entropy is used as the fundamental apparatus to estimate and control the events in a system. In any information channel, the recipient of messages is in complete uncertainty of the upcoming information if all possible states of the message are equally probable. The interpretation provided by the information theory is as follows: the anticipated message which is about to come has maximal entropy if there is no a priori expectation of what is coming. With every new message arrived, the clarity about what is going to come next may increase, thus reducing the uncertainty, thus entropy as its measure.

c) Physics

In classical physics, the second law of thermodynamics uses the entropy of a physical system to characterize the free energy; that is the remaining after work energy which cannot be used to do more physical work. The free energy exists in a system where all microscopic particles are in chaotic state and there is no flow (gradient) of energy. Again, in an isolated system any activity increases the entropy until it comes to the steady state of the

system with no gradient of energy flow. The relationship between information and physical entropy is crucial in understanding of processes in biological systems by shedding some light on possible explanation of the biological aspect of perception of time in view of information and energy. The key point here is as follows. Obtaining information is about removing uncertainty: unstructured knowledge gains a structure which means that the entropy decreases. To get information is impossible without adding some energy which increases the physical entropy. The source of energy and information channel are parts of a closed system. Due to the second law of thermodynamics the entropy of a closed system cannot decrease, thus the amount of obtained information measured as entropy cannot exceed the entropy of the source.

d) Energy and information

In reality, the used energy is an upper bound of the information content. One cannot read a book without applying some energy such as light! The more energy is brought in when an object is studied under a microscope the more detailed information can be gained about the object. This principle of complementary role of information in any physical and biological process is a centerpiece of this discussion where entropy, negative entropy (*negentropy*) and information are considered. So, the perception of time can be associated with the intensity of energy-information exchange. The decline in energetic processes in biological systems leads to slower information accounting. To understand how the entropy changes we should consider dynamical systems that have a tendency to evolve to chaotic states. The appropriate apparatus has been developed in the framework of Kolmogorov-Sinai (KS) entropy. The relationship between time and entropy is expressed by the notion of arrow of time. In the words of Sir Arthur Eddington, 'Entropy is time's arrow'.

e) Entropy in life

One of the most prolific observations concerning life, entropy and information can be found in the lecture by E. Schrodinger presented by him in 1944 [6]. "Every process, event, happening in a world, everything that is going on in Nature means an increase of the entropy of the part of the world where it is going on. Thus, a living organism continually increases its entropy - or, as you may say, produces positive entropy and thus tends to approach the dangerous state of maximum entropy, which is of death. It can only keep aloof from it, i.e., alive, by continually drawing from its environment negative entropy which is something very positive as we shall immediately see. What an organism feeds upon are negative entropy. Or, to put it less paradoxically, the essential thing in metabolism is that the organism succeeds in freeing itself from all the entropy it cannot help producing while alive.

"Here, the notion of negative entropy is the one that was later associated with information and being termed as negentropy by L Brillouin [7].

Brain Entropy

The brain uses knowledge of elapsed time to anticipate sensory events and to prepare appropriate actions. Time perception is based on some neural bases. Also, as it is mentioned in [8], “timing is also critical to almost every behavior we engage in, from neural computation to driving a car to playing piano.” There are a few approaches and definitions of the brain entropy. It can be associated with the non-stationary metric of the brain processes (EEG based metric) but it also can be applied to the connectivity of different parts of the brain. There are, at least, two general approaches in calculation of BEN: one is applied to the time series data obtained from EEG while the other one is based on calculation of entropy of the brain clusters discovered in the process of functional MRI (fMRI) based on so called BOLD technology. A number of variants of the BEN implementation have been published. Among those, there are transfer BEN and functional entropy. The functional entropy, for example, was defined to be used with fMRI data characterizing the brain connectivity changing with age. The cognitive phenomena originate from the interaction among several mutually interconnected, specialized brain regions, which exchange information via long range synapses. It was shown [9] that the randomness of brain activity decreases with age, which implies a decrease of the entropy in time domain. However, the functional entropy increases with age. We should note that the decrease or increase of the entropy may be characterized as associated with negentropy, a complement to the brain’s thermodynamical entropy.

Entropy in the fMRI study

De Araujo et al. [2] suggested to use Shannon entropy to analyze fMRI time-series. The general approach to calculation of the brain entropy is based on the entropy measures applied to a real valued series. Consider N discrete intervals (or amplitude levels) $I_k=1/N$ which are selected in such a way that every value from a series belongs to some interval I_j . The frequency p_k of the values from a series X belonging to k -th interval I_k can be expressed as follows:

$$P_k = \frac{\text{No. values of Series within } I_k}{\text{No. all values of Series}}$$

Now the Shannon entropy H of a series X of length N is defined as:

$$H(X) = - \sum_{k=1}^N p_k \cdot \log(p_k)$$

Later, this approach was extended by using Tsallis entropy [10]. For a series X of discrete values, the Tsallis entropy of order q is defined as:

$$H_q(X) = \frac{1}{q-1} \cdot \left(1 - \sum_{k=1}^N p_k^q \right)$$

Later, a practical method to calculate the BEN was proposed to address the computational complexity of the BEN calculation. The problem with the Shannon entropy as applied to the brain activity is that many samples should be collected to obtain a sufficient accuracy of the BEN assessment. The method of Approximate Entropy, ApEn was first suggested by Pinkus S [11]. Now it is predominantly used in analysis of brain connectivity and functional state.

Entropy of Brain Increases with Age

In this research, we discuss a hypothesis of Perception of Time as a metric associated with the brain entropy. The brain entropy characterizes the accessibility of stored past events. In the case of reduced brain alertness, the more distorted the status of the brain is the more likely the closest past event will not be found – the intervals between stored events will increase. Dynamics of the brain activity is changing during the human’s lives. The practical observation and common belief are that the pace of time (a.k.a. Perception of Time) is increasing as human life goes on. The PT hypothesis will be substantiated, if it would be found that the brain entropy does change with time. Indeed, it was shown, very substantively, in the research by Yao Y et al. [9] who evaluated the Brain Entropy for a large group of people of different ages. As mentioned in their report, the entropy was used “to characterize intrinsic ageing properties of the human brain. Analysis of fMRI data from a large dataset of individuals, using resting state BOLD signals, demonstrated that a functional entropy associated with brain activity increases with age”. The computational model used in the research is illustrated by (Figure 2).

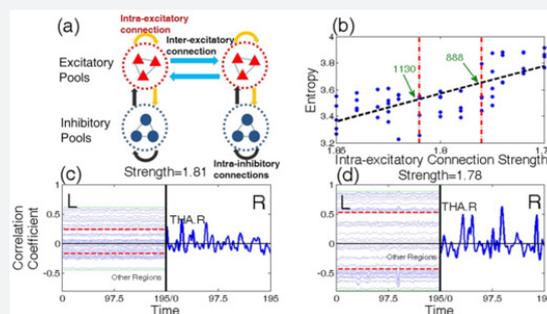


Figure 2: Computational model.

Figure 3 illustrates the obtained results of experiments for a large group of people of different ages. The experiments were based on capturing the BOLD (Blood-oxygen-level-dependent imaging) signals which is the focus in the fMRI analysis. A mean rate of increase of the entropy of 0.0013 bits/year was found from the data. Panel (b) contains a plot of the running average of the entropy, versus age, with a window of width of 25 years adopted. Panels (c) and (d) plot the entropy versus age of males and females. Males have a lower initial value of the entropy than

females, but a faster mean rate of increase. The fact that the brain entropy increases with age can be considered as an indirect confirmation of the hypothesis that the humanly perceived time is running out with ever increasing speed and that this fact can be considered as an indirect confirmation of the role of status of the brain as measured by BEN. We presume that the BEN metric can be used in the diagnostics of other time assessment disorders experienced by some patients.

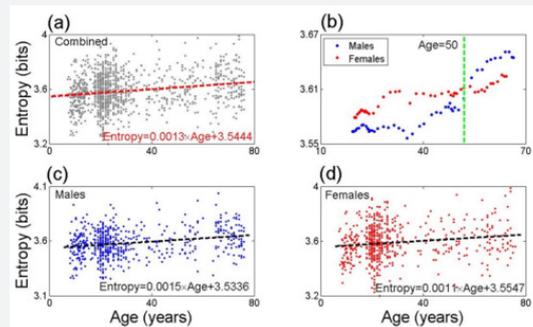


Figure 3: Functional Entropy vs Age.

Event Driven Model of Time

An Event Driven model

The perception of time durations is crucially bound up with human's memory. It is essentially our memory of an event (and perhaps, even more specifically, our memory of the beginning and end of the event) that allows us to form a perception of, or a belief in, its duration. We infer, perhaps, subconsciously, the duration of an event from our memory that is of how far in the past something occurred, of how long ago the beginning and end of the event occurred. It is not clear whether this is done by some measure of the strength of a memory trace that persists over time (the strength model of time memory), or by an inference based on associations between the event and other events whose date or time is known (the inference model). Among many possible different options of modeling the event driven mechanism, we consider here a simple lifetime elastic band model of Brain Entropy.

The following assumptions have been made:

- i. Time interval is measured as relative to the previous event.
- ii. All previously stored events are presumed to be sorted by the strength of impression.
- iii. The strength of the event corresponds to the probability of being recalled.
- iv. Only strong impressive events can be identified – thus, defining the time interval between the events.

Short Term Memory Experiment is planned as follows:

- a) Brain is set in Resting State (Neuron cells are in uncorrelated random activation).
- b) Create (imagine) a sequence of events (e.g., kettle whistle, light turned on, a word said, etc.), or simply pronounced words.
- c) Each event is registered as a data structure Event_ID {Event Name, Start TIME}.
- d) Query 1: How much time has passed since a specific randomly selected event?
- e) Query 2: Arrange events timewise.
- f) Expected result: On average, event time interval will be assessed as shorter – for uncorrelated clusters.

The experimenter will arrange all the previous events with respect to the time of arrival. Events are stored in designated locations (neuron clusters). With a high entropy, some locations may not be acceptable, or weakened, or become dead.

The expected results:

- i. On average, the access to a remote event becomes shorter than it has been originally – the brain time seems to be compressed.
- ii. The number of lost (skipped, unregistered, dead) events increases with the entropy (uncertainty, lack of correlation) grow.
- iii. The following illustration is an example of how with ageing, the perceived time interval expands to encompass a larger real time interval.

The data collected due to the modeling as above, can be used to define a model of human lifetime as perceived by humans. Here, in the beginning of life, the perception of time by brain is more or less adequate but starting from some moment in life the perceived time becomes gradually slow down. For example, at a specific moment in life, the perceived time interval can become significantly skipping a number of events.

As mentioned above, due to the Schrodinger [20] model of life measured in the thermo-dynamical units the increase in entropy characterizes the move from order to disorder. When entropy reaches its maximal level, it characterizes the physical death of brain. This fact can be interpreted in the context of the brain status going from an organized, correlated mode of its connectivity to more irregular, uncorrelated activation of brain clusters. Thus, we assume that the Brain entropy can be presented as a function of age: BEN (Age).

“Elastic band” model of perceived time

The Real (outside of the human body) Time, RT, is a function of perceived time, PT: RT (PT)

In its turn, PT is a function, Q, of Brain entropy, BEN,

$$PT = Q(BEN). \tag{A}$$

Here is an assumption that the perception of time can be considered by an analogy with an elastic band. Another simple assumption: it can be presented using an exponential function exp():

$$PT = RT - k * \exp(BEN)$$

where $k = 0$, if $PT < PT_{critical}$

$= 0$, otherwise

If RT grows faster than PT, like, for example,

$$RT = k_1 * (\exp(k_2 * PT) - 1)$$

In more general form, the RT should be presented as a polynomial function, such as

$$F(t) = a_0 + a_1 * t + a_2 * t^2 + \dots + a_n * t^n$$

This polynomial can be found by using a non-linear regression.

By applying the inverse function $F^{-1}(t)$, we can hypothesize about the perceived time related to the real (outside the brain) time:

$$PT = F^{-1}(t)RT \tag{V.A}$$

Then, we should resolve the RT from PT.

$$RT = PT + k * \exp(BEN) \tag{V.B}$$

EEG Based Modeling

The results presented so far concern the analysis of brain entropy based on the fMRI study. It should be mentioned here that the MRI technique does provide accurate localization of the activated brain clusters but performing such study requires much longer time to observe the brain status. We would like to develop the methods of studying BEN using mostly an EEG technique. Such an analysis would not only accelerate the process of measuring the brain activity but also shed light on the instantaneous BEN changes during the experiments. Here is a suggested computational path:

- a) Present the events such as auditory, visual, and other signals.
- b) Collect the EEG signals from the designated parts of the testers' heads.
- c) Convert the EEG signals into the set of activated areas of the brain.
- d) Calculate the brain entropy using the levels of activation of different brain clusters.

The method of converting the EEG signals as functions of time into the spatial information about the activated areas of the brain requires the inverse modeling of the clustered brain. A method appropriate for this EEG based approach was developed earlier and presented in a preprint: “Inverse Problem’s Solution Using Deep Learning: An EEG-based Study of Brain Activity” [15]. A further development of this approach was also presented in a paper published later [1].

1. Cortex clusterization

Figure 4 illustrates the selected clusters identified based on the collected EEG data.

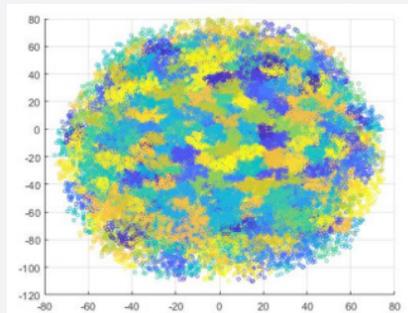


Figure 4: clusterization cortex used in the modeling.

II. Model of cortex activity

The following model of cortex activity was used in the analysis:

1. Given is a set, S , of N sources of activation inside the cortex area $G(x, y, z)$. The sources represent the neurons locations:

$$S = \{(sx_i, sy_i, sz_i): (sx_i, sy_i, sz_i) \in G; i \in [1:N]\} \tag{1}$$

2. A set, E , of $M < N$ locations of sensors (electrodes) applied to the boundary surface ∂G :

$$E = \{(ex_j, ey_j, ez_j): (ex_j, ey_j, ez_j) \in \partial G; j \in (1:M)\} \tag{2}$$

3. The brain's electrical field $u(x,y,z)$ is modeled as elliptical (Laplace) equation:

$$\begin{aligned} Lu &= 0, & (x, y, z) \in G, \\ u &= g(x, y, z); & (x, y, z) \in \partial G \end{aligned} \tag{3}$$

where $g(x, y, z)$ is the boundary conditions – the electroencephalographic potentials (EEG) on the surface of the scalp.

4. The method of fundamental solutions (MFS) [13,14] is used to approximate the model as the linear combination of the basic functions of the elliptical equation.

III. Elements of the proposed method

Below, a few elements of the suggested approach are presented.

1. Create a neuron activation model and calculate the electrode potentials, ElPot, for a given set of fired (activated) neurons, NeuronSet – forward model.
2. Run the forward model for random sets of activated neurons (and/or their clusters) – collect the dataset by mapping activated neurons/clusters onto electrode potentials:
NeuronSet \rightarrow ElPot.
3. Prediction: Given an observation of electrode potentials, ElPot_Obs, find the possible corresponding clusters of the activated cortex neurons, NeuronSet_Obs; use the dataset from step 2 to search through – inverse solution.
4. Implement the inverse model by using the Deep Neural Network (DNN): training the model with the ElPot_Obs as the input and NeuronSet as the output classes.
5. Provide validation and testing of the DNN as above.
6. Estimate the hypothesis \mathcal{H} : the DNN in Step 4 generalizes beyond the dataset used for the training.

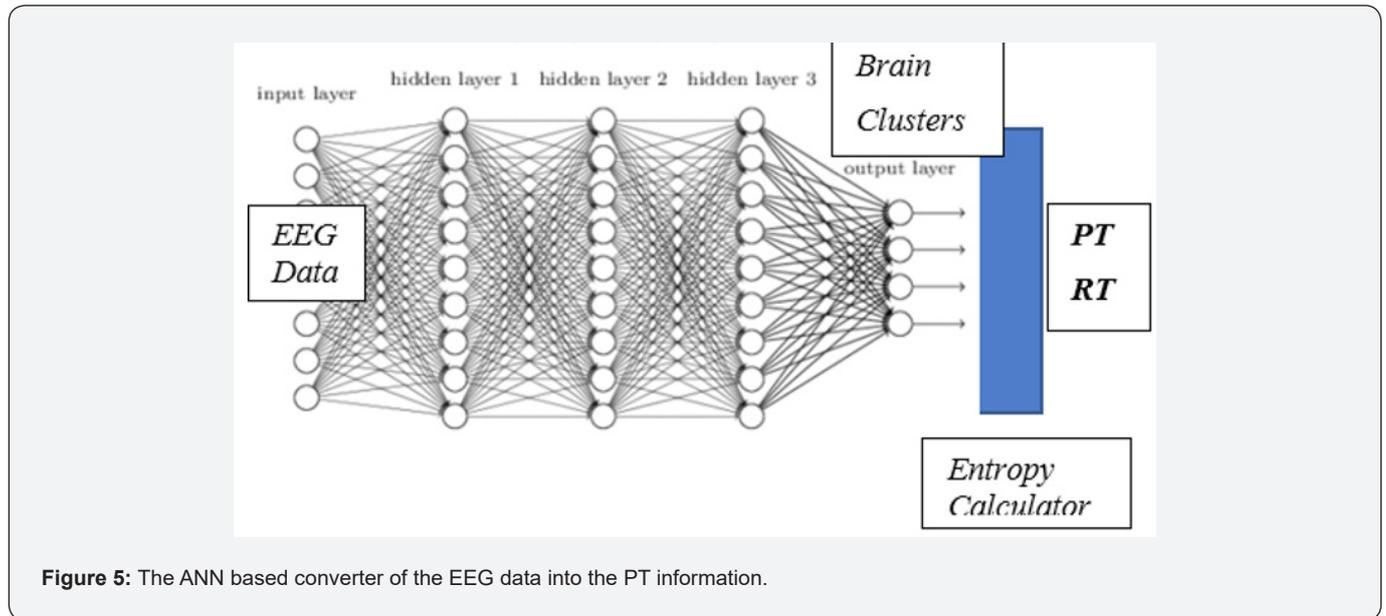


Figure 5: The ANN based converter of the EEG data into the PT information.

IV. Deep Learning model

As shown on Figure 5, the deep fully connected Artificial Neural Network was used to convert the real time EEG data (input layer) into the levels of activation of different brain clusters (output layer). The ANN output values are passed to the function of Entropy Calculator that produces the hypothetical perceptual time estimates (PT, RT) based on the above formulas (V.A) and (V.B). In the Forward Mode, the Deep Learning model is used to convert the EEG registered non-stationary data into the levels of activation of different clusters identified on the cortex. Then, the functional entropy is calculated which is used to define the hypothetical perception time parameters. The DL model should be trained before being used in the forward mode. It starts with

collection of data reflecting the effect of randomly activated clusters onto the electrode potentials. The dataset is created here based on the forward modeling of the assumed model of neuron activity. The dataset, then, is used for the Deep Learning model (a) design; (b) training, (c) validation and (d) prediction. The limited experiments performed so far concerned clusters with 50 000 neurons. The clusters activity was imitated to produce various combinations of the EEG electrode potentials. These generated data was used to train the DL model. Afterwards, the DL model was ready to perform the prediction of what brain clusters were activated when the observed non-stationary EEG potentials were used as the DL inputs. More specific details can be found in [15].

Conclusion

The human's everyday activity has a temporal dimension – it goes along with time as we perceive it. This perception of time intervals is subjective and depends on the cognitive processes in the individual brains.

Here we have discussed a hypothesis concerning the relationship between perception of time and the brain entropy. The brain entropy calculation is one of the most significant means used in neuroscience recently.

Assuming that the changes of the brain entropy may affect the human's ability to memorize the events registered by the brain, our analysis considers the event-driven model as an elastic band under stretching going on along with the human's life. The relationships are suggested between the perceived time and the objective time of human's life. The experiments concerning this research are at the preliminary stage, although the overall approach has been developed in the field of the Deep Learning applied to the nonstationary data series of the EEG measurements. One of the future research directions that should be mentioned here is a subject of rather sociological than technical or medical nature: If the persistence of time is specific for each of the communicated humans of different ages, brain activity levels, and individual characteristics, then how these differences affect their social interactions? It seems like the whole societal groups should be considered as affected by those differences in their perception of time. These groups of interacting individuals may be considered as examples of, what we can call "polychronic societies".

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