NeuCube EvoSpike Architecture for Spatio-temporal Modelling and Pattern Recognition of Brain Signals

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Abstract. The brain functions as a spatio-temporal information processing machine and deals extremely well with spatio-temporal data. Spatio- and spectro-temporal data (SSTD) are the most common data collected to measure brain signals and brain activities, along with the recently obtained gene and protein data. Yet, there are no computational models to integrate all these different types of data into a single model to help understand brain processes and for a better brain signal pattern recognition. The EU FP7 Marie Curie IIF EvoSpike project develops methods and tools for spatio and spectro temporal pattern recognition. This paper proposes a new evolving spiking model called NeuCube as part of the EvoSpike project, especially for modeling brain data. The NeuCube is 3D evolving Neurogenetic Brain Cube of spiking neurons that is an approximate map of structural and functional areas of interest of an animal or human brain. Optionally, gene information is included in the NeuCube in the form of gene regulatory networks that relate to spiking neuronal parameters of interest. Different types of brain SSTD can be used to train a NeuCube, including: EEG, fMRI, video-, image- and sound data, complex multimodal data. Potential applications are: EEG -, fMRI-, and multimodal brain data modeling and pattern recognition; Brain-Computer Interfaces; cognitive and emotional robots; neuro-prosthetics and neuro-rehabilitation; modeling brain diseases. Analysis of the internal structure of the model can trigger new hypotheses about spatio-temporal pathways in the brain.

Keywords: evolving neurogenetic brain cube, spatio/spectro-temporal brain data, pattern recognition, spiking neural networks, gene regulatory networks, computational neuro-genetic modelling, probabilistic modeling, personalized modeling, EEG, fMRI.

1 Spatio/ Spectro-temporal Information Processes in the Brain

1.1 Spatio-temporal Information Processes in the Brain

The brain is a complex integrated spatio-temporal information processing machine. An animal or human brain has different functional areas that are spatially distributed

in a constrained 3D space, e.g. fig.1. When the brain processes information, either triggered by external stimuli, or by inner processes, such as visual-, auditory-, somatosensory-, olfactory-, control-, emotional-, or all together, complex spatio-temporal paths are activated and patterns are formed across the whole brain, e.g. fig.2.

Fig. 1. Structural/functional areas of the brain are spatially distributed

Fig. 2. Spatio-temporal signaling paths in the brain

Example 1 (from [3]): ‘...the language task involves transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (Brodmann’s area 41), then to the higher-order auditory cortex (area 42), before it is relayed to the angular gyrus (area 39). Angular gyrus is a specific region of the parietal-temporal-occipital association cortex, which is thought to be concerned with the association of incoming auditory, visual and tactile information. From here, the information is projected to Wernicke’s area (area 22) and then, by means of the *arcuate fasciculus*, to Broca’s area (44, 45), where the perception of language is translated into the grammatical structure of a phrase and where the memory for word articulation is stored. This information about the sound pattern of the phrase is then relayed to the facial area of the motor cortex that controls articulation so that the word can be spoken. It turned out that a similar pathway is involved in naming an object that has been visually recognized. This time, the input proceeds from the retina and LGN (lateral geniculate nucleus) to the primary visual cortex, then to area 18, before it arrives to the angular gyrus, from where it is relayed by a particular component of arcuate fasciculus directly to Broca’s area, bypassing Wernicke’s area’ [end of citation].

The example above shows that the brain processes information through the activation of complex spatio-temporal pathways involving many areas. Can this principle be modeled in a computer model, resulting in an improved accuracy of brain signal pattern recognition and new knowledge discovered?

Many other studies of spatio-temporal pathways in the brain have been conducted, e.g. birdsong learning [14].

1.2 Measuring Spatio/Spectro Temporal Brain Data

Much of the measured brain data is indeed spatio-temporal. The most common types are EEG [10,15,41] and fMRI data [58] (examples are shown in figs.3 and 4 respectively).

Fig. 3. EEG data recorded with the use of Emotive

Fig. 4. fMRI data (from <http://www.fmrib.ox.ac.uk>)

Many other techniques for collecting brain spatio-temporal data exist [19,9,6].

1.3 Spatio-temporal Brain Gene Data

Spatio-temporal activity in the brain depend on the internal brain structure, on the external stimuli and also – very much on the dynamics at the gene-protein level. The Allen Human Brain Atlas (www.brain-map.org) of the Allen Institute for Brain Science (www.alleninstitute.org) has shown that at least 82% of the human genes are expressed in the brain. For 1000 anatomical sites of human brains 100 mln data points are collected that indicate gene expressions of each of the genes and underly the biochemistry of the sites. Different genes express as mRNA, microRNA and proteins differently in different areas of the brain and are involved in all information processes, from simple spiking activity, to perception, decision making and emotions. For example, in [66] it is suggested that both the firing rate (rate coding) and spike timing depends on microRNAs that play a role in fast and slow dynamics and adaptive sensorimotor responses controlled by the cerebellar nuclei. Spatio-temporal patterns of population of Purkinji cells are shaped by activities in the molecular layer of interneurons. Functional connectivity develops in parallel with structural connectivity during brain maturation - a growth-elimination process (synapses are created and eliminated) depending on gene expression. Postsynaptic AMPA-type glutamate receptors (AMPA) mediate most fast excitatory synaptic transmissions and are crucial for many aspects of brain function, including learning, memory and cognition [25,3]. The spiking activity of a neuron may affect as a feedback the expressions of genes [66]. As pointed in [66] on a longer time scale of minutes and hours the function of neurons may cause changes of the expression of hundreds of

genes transcribed into mRNAs and also in microRNAs, which makes the short-term, the long-term and the genetic memories of a neuron linked together in a global memory of the neuron and further - of the whole neural system.

All the above facts and the numerous studies of gene activities related to brain spiking activity suggest that genes have to be taken into account when modeling brain data.

2 Spiking Neural Networks for SSTD Modelling and Pattern Recognition

The human brain has the amazing capacity to learn and recall patterns at different time scales, ranging from milliseconds, to years and possibly to millions of years (e.g. genetic information, accumulated through evolution). Thus the brain is the ultimate inspiration for the development of new machine learning techniques for brain SSTD modeling. Indeed, brain-inspired Spiking Neural Networks (SNN) [26,27,8,20,21] have the potential to learn SSTD by using trains of spikes (binary temporal events) transmitted among spatially located synapses and neurons. Both spatial and temporal information can be encoded in an SNN as locations of synapses and neurons and time of their spiking activity respectively.

Models of single neurons as well as computational SNN models, along with their respective applications, have been already developed [1,5,7,35,42,65], including evolving connectionist systems and evolving spiking neural networks (eSNN) in particular [35]. eSNN learn data incrementally by one-pass propagation of the data via creating and merging spiking neurons [35,65]. In [65] an eSNN is designed to capture features and to aggregate them into audio and visual perceptions for the purpose of person authentication.

Recently some new techniques have been developed as part of the EvoSpike project (<http://ncs.ethz.ch/projects/evospike>) and other projects that allow the creation of new types of computational models to deal with SSTD [40], e.g.: SPAN [45,46]; deSNN [13]; reservoir eSNN [47,55,57]. Applications included moving object recognition [40,13,34], sign language recognition [53], EEG pattern recognition [48].

Still, the current methods and systems for SSTD do not reflect on the brain structure and functionality which may be beneficial when modeling brain SSTD, for brain pattern recognition and consequently for understanding brain spatio-temporal connectivity. There are some functional models of the brain, such as Izhikevich's [33] and the IBM Modha's models, but they do not suggest methods for brain SSTD pattern recognition, neither they include a broader genetic information.

The proposed here NeuCube Architecture is aiming at bringing the two research lines together through the creation of SNN that reflect on the brain structure and functionality with the hypothesis that it can be efficiently used for brain SSTD modeling and pattern recognition along with the discovery of new knowledge about brain spatio-temporal connectivity under different conditions.

3 The Proposed NeuCube Architecture

3.1 Overall Architecture and Main Principles

The main idea is to support the creation of multi-modular integrated systems, where different modules, consisting of different neuronal types and genetic parameters *correspond* in a way to different parts of the brain and different functions of interest (e.g.: vision; sensory information processing; sound recognition; motor-control) and the whole system works in an integrated mode for brain signal pattern recognition. A concrete model, built with the use of the NeuCube architecture, would have a specific structure and a set of algorithms depending on the problem and the application, e.g.: classification of EEG signals; recognition of fMRI data; BCI; emotional cognitive robotics; modeling AD.

A block diagram of the general EvoSpike NeuCube architecture is shown in fig.5. It consists of the following modules: input information encoding module; NeuCube module; output module; gene regulatory networks (GRN) module. The input module transfers input data into trains of spikes when sound/image or other sensory data is processed. EEG-, fMRI and other brain data is directly entered into the main module – the NeuCube.

Fig. 5. A schematic diagram of a general NeuCube architecture, consisting of: input encoding module; NeuCube module; output function module; gene regulatory networks (GRN) module (optional)

The NeuCube is an approximate map of relevant for the study brain regions, along with relevant genetic information, as a 3D spiking neuronal structure. An initial NeuCube structure can include known connections between different areas of the brain. There are two types of SSTD used for both training a particular NeuCube and to recall it on new data:

- (a) SSTD, measuring the activity of the brain (e.g. EEG, fMRI) when certain stimuli are presented. This data is entered to corresponding spatially located areas of the Cube;
- (b) Direct stimuli data, e.g. sound, spoken language; video data; tactile data; odor data etc., which are first encoded into spike trains in the input module.

A NeuCube architecture is three-tier, consisting of a NeuCube module at the middle level, gene regulatory networks (GRN) at the lowest level, and a higher level evaluation (classification) module. The GRN control parameters of neurons from the NeuCube. Genes from the GRN are also affected by spiking activity of these neurons. Neurons from the NeuCube are connected to neurons of the output module in a two-way mode, so that the state of the Cube can be recognized/classified/interpreted in the Output Module and the result of this can also influence further activity of the neurons in the Cube as a feedback.

Different types of neurons and learning rules can be used in different areas of the architecture which is evolving. While a NeuCube Architecture has an initial structure, new neurons and connections are created from incoming data when this is needed. The structure and the functionality of a NeuCube Architecture evolve in time from incoming data.

Learning in the NeuCube Architecture is performed in two stages:

- Unsupervised training of a NeuCube, where SSTD is entered into relevant areas of the cube over time and unsupervised learning is used to establish the connection weights. The NeuCube will learn to activate similar spiking trajectories when similar input stimuli are presented – a *polychronisation* effect [32].
- Supervised training of the output module, where the same SSTD used for training is now propagated again through the trained NeuCube and output neurons are trained to classify the state of the cube into pre-defined labels (or output spike sequences). As a special case, all neurons from the NeuCube are connected to every output neuron. Feedback connections from output neurons to neurons in the NeuCube can be created for reinforcement learning.

Memory of a NeuCube Architecture is represented as a combination of: (a) Short-term memory, represented as changes of the PSP and temporary changes of synaptic efficacy; (b) Long-term memory, represented as a stable establishment of synaptic efficacy; (c) Genetic memory, represented as a change in the genetic code and the gene/ protein expression level as a result of the above short-term and long term memory changes and evolutionary processes.

More detailed description of a realization of the NeuCube Architecture is given below.

3.2 Input Encoding Module

This module converts input data into trains of spikes. The spike trains will be directed to the corresponding areas of the NeuCube. Temporal spike coding (rather than rate coding) is used following biological facts (e.g. [50,51]). Two methods are used to transfer continuous SSTD into spike trains.

3.2.1 Population Rank Coding

Continuous value input data is transferred into spikes so that the current value of each input variable (e.g. pixel, EEG channel, voxel) is entered into a population of neurons that emit spikes based on their receptive fields [4-6] – fig.6a. This is suitable when the input data is presented as a sequence of frames. If this is a frame (a vector) of EEG data of 64 channels, for example, each channel value is entered into a population of spiking neurons from the NeuCube module that are spatially located. These neurons transfer the channel value into a sequence of spikes generated based on the membership of this value to the receptive fields of the neurons (fig.6a). If there is no sufficient membership degree to any of the existing neurons, new neurons are generated (evolved) to accommodate this value.

3.2.2 Address Event Representation (AER)

This is based on thresholding the difference between two consecutive values of the same input variable over time as it is in the artificial retina [12] - fig.6b. This is suitable when the input data is a stream and only the changes in consecutive values are processed.

Fig. 6. (a) Population rank order coding of input information; (b) Address Event Representations (AER) of the input information (e.g. [12])

The input information is entered either on-line (for on-line, real time applications) or as a batch data. The *time* of the input data is in principal different from the internal *time* of information processing in the NeuCube.

3.3 The NeuCube Module

3.3.1 The Structure

The structure of the NeuCube is a 3D approximate map of brain areas of interest. Small world connections are used to initialize the connections, where neurons within a functional area of interest from the cube (e.g. visual area) are more densely connected than neurons across areas, still depending on the distance between the neurons [62]. Prior connections can be set based on prior knowledge. New neurons are created to accommodate data that is not possible to accommodate in the existing neurons following the ECOS principle [35]. The new neurons are connected with the rest following initially the small-world principle.

Input information in the NeuCube is entered not to arbitrarily selected neurons (as it is in the reservoir computing [42,62]), but to context dependent one from the NeuCube, e.g. visual information is entered into the neurons in the NeuCube that correspond to the visual cortex. In this way the cube has a meaningful structure that can be understood in terms of spatio-temporal pathways.

In the NeuCube each area can in principally use different neuronal models and learning algorithms. As a first implementation here, we use a probabilistic leaky integrate and fire model (LIFM) [39] and STDP learning rule [59].

3.3.2 The Neuronal Model

Fig. 6c and d illustrate the structure and the functionality of the LIFM [19-21]. The neuronal post synaptic potential (PSP), also called membrane potential $u(t)$, increases with every input spike at a time t , multiplied to the synaptic efficacy (strength), until it reaches a threshold θ . After that, an output spike is emitted and the membrane potential is reset to an initial state. Between spikes, the membrane potential leaks, which is defined by a temporal parameter τ .

Fig. 6. (c) The structure of the LIFM

(d) functionality of the LIFM

In the probabilistic neuronal model [39] in addition to connection weights $w_{j,i}(t)$, a probabilistic spiking neuron model has the following three probabilistic parameters:

- A probability $p_{c,j,i}(t)$ that a spike emitted by neuron n_j will reach neuron n_i at a time moment t through the connection between n_j and n_i . If $p_{c,j,i}(t)=0$, no connection and no spike propagation exist between neurons n_j and n_i . If $p_{c,j,i}(t) = 1$ the probability for propagation of spikes is 100%.
- A probability $p_{s,j,i}(t)$ for the synapse $s_{j,i}$ to contribute to the $PSP_i(t)$ after it has received a spike from neuron n_j .
- A probability $p_i(t)$ for the neuron n_i to emit an output spike at time t once the total $PSP_i(t)$ has reached a value above the PSP threshold (a noisy threshold).

The total $PSP_i(t)$ of the probabilistic spiking neuron n_i is now calculated using the following formula [39]:

$$PSP_i(t) = \sum_{p=t_0, \dots, t} \left(\sum_{j=1, \dots, m} e_j f_1(p_{c,j,i}(t-p)) f_2(p_{s,j,i}(t-p)) w_{j,i}(t) + \eta(t-t_0) \right)$$

where: e_j is 1, if a spike has been emitted from neuron n_j , and 0 otherwise; $f_1(p_{c,j,i}(t))$ is 1 with a probability $p_{c,j,i}(t)$, and 0 otherwise; $f_2(p_{s,j,i}(t))$ is 1 with a probability $p_{s,j,i}(t)$,

and 0 otherwise; t_0 is the time of the last spike emitted by n_i ; $\eta(t-t_0)$ is an additional term representing decay in the PSP_i . As a special case, when all or some of the probability parameters are fixed to “1”, the above probabilistic model will be simplified and will resemble the well known IFM.

The probabilistic model of a neuron is flexible to represent different types of neuronal models depending on the probabilistic parameters chosen, along with being suitable for the functional link with genes and GRN [39].

3.3.3 The Learning Rule

It has been demonstrated that a SNN that utilises probabilistic neuronal model can learn better SSTD than traditional SNN with simple IFM, especially in a noisy environment [53-56]. The effect of each of the above three probabilistic parameters on the ability of a SNN to process noisy and stochastic information was studied in [57,55].

The STDP learning rule [59], used here to train the NeuCube, utilizes Hebbian plasticity [24] in the form of long-term potentiation (LTP) and depression (LTD) (fig.7a). Efficacy of synapses is strengthened or weakened based on the timing of post-synaptic action potential in relation to the pre-synaptic spike. If the difference in the spike time between the pre-synaptic and post-synaptic neurons is negative (pre-synaptic neuron spikes first) then the connection weight between the two neurons increases, otherwise it decreases. Through STDP, connected neurons learn consecutive temporal associations from data and new connections are also evolved. Pre-synaptic activity that precedes post-synaptic firing can induce long-term potentiation (LTP), reversing this temporal order causes long-term depression (LTD). Other spike time unsupervised learning rules can be in principle used instead of STDP, depending on the problem in hand.

3.3.4 Evolvability of the NeuCube

Initial structure of the NeuCube is preliminary defined based on the brain data available and the problem. But the structure is also evolving through the creation of new neurons and new connections based on the ECOS principles [35]. If new data do not activate sufficiently existing neurons, new neurons are created and allocated to match the data along their new connections.

3.4 The Output Module

During the training of the NeuCube with SSTD, a mapping of the input data into spatio-temporal patterns of connectivity and spiking activity pathways of the NeuCube is learned. After training, these NeuCube patterns are learned to be associated with known classes in a classifier of the Output Module, or actions are produced for motor control tasks. Feedback connections from the Output Module to the NeuCube are possible to establish for reinforcement learning.

In our first realization, all spiking neurons from the NeuCube are connected to each of the output neurons. Two different methods are developed in the EvoSpike project: deSNN for classification of NeuCube states; SPAN for generating motor control signals in response to certain patterns of activity of the NeuCube.

3.5.1 deSNN for Fast, On-Line Classification Based on AER Principle

The dynamic eSNN (deSNN) [13] combines rank-order and temporal (e.g. STDP or SDSP) learning rules. The initial values of synaptic weights are set according to the rank-order learning assuming the first spikes in the NuCube are more important than the rest. The weights are further modified to accommodate following spikes from the NeuCube activated by the same SSTD stimulus pathway, with the use of a temporal learning rule – STDP (or SDSP).

The rank-order learning rule [61,60] uses important information from the input spike trains – the rank of the first incoming spikes on the neuronal synapses (fig.7b). It establishes a priority of inputs (synapses) based on the order of the spike arrival on these synapses for a particular pattern, which is a phenomenon observed in biological systems as well as an important information processing concept for some problems, such as computer vision and control [4,61,51]. This type of learning has several advantages when used in SNN, mainly: fast, one- pass, learning (as it uses the extra information of the order of the incoming spikes) and asynchronous data entry (synaptic inputs are accumulated into the neuronal membrane potential in an asynchronous way). The postsynaptic potential of a neuron i at a time t is calculated as:

$$PSP(i, t) = \sum mod_{order(j)} w_{j,i}$$

where: mod is a modulation factor; j is the index for the incoming spike at synapse j,i and $w_{j,i}$ is the corresponding synaptic weight; $order(j)$ represents the order (the rank) of the spike at the synapse j,i among all spikes arriving from all m synapses to the neuron i . The $order(j)$ has a value 0 for the first spike and increases according to the input spike order. An output spike is generated by neuron i if the PSP (i,t) becomes higher than a threshold $PSP_{Th}(i)$. During the training process of a classifier, for each training input pattern (e.g. a spiking trajectory of the NeuCube) the connection weights are calculated based on the order of the incoming spikes [61,65]: $\Delta w_{j,i}(t) = \frac{1}{mod_{order(j,i)(t)}}$

Fig. 7. a,b: (a) An example of synaptic change in a STDP learning neuron [59]; (b) Rank-order learning neuron

3.4.2 The SPAN Algorithm for Spike Pattern Association and Motor Control Applications

SPAN is an algorithm for both classification and spike pattern association [44-46]. The whole spiking pattern of the NeuCube is learned here, rather than spike by spike

as it is in the deSNN. Delta rule is used for the purpose [64]. SPAN learns to generate an output spike at a certain time, or a pattern of temporally distribute spikes over time, when a certain input spatio-temporal pattern of spikes (e.g. spiking sequence from the NeuCube) is recognized. Two algorithms are developed, one for batch mode learning [46], and one for incremental learning [45]. SPAN is a suitable algorithm for *control applications*, so that when a certain pattern is recognized, a series of motor control signals are emitted at different times on one or on several outputs. In principle, SPAN is a further development of a class of algorithms, including: ReSuMe [49]; Chronotron [16]; Tempotron [23].

4 The Gene Regulatory Network (GRN) Module

4.1 How Do Genes Affect the Spiking Activity of the NeuCube Architecture?

The GRN module from fig.5 uses as a main principle the analogy with biological facts about the relationship between spiking activity and gene/protein dynamics in order to control the learning and spiking parameters in a SNN. Biological support of this can be found in numerous publications (e.g. [3,25,66]). We illustrate this with the following example.

Example 2: In [38] the dramatic effect of a change of single gene, that regulates the τ parameter of the LIF neurons, on the spiking activity of the whole SNN cube of 1000 neurons, is shown in fig.8.

Fig. 8. A single gene expression level over time can affect the pattern of activity of a whole cube of 1000 neurons (from [38]). The gene controls the τ parameter of all 1000 LIF neurons over a period of five seconds. The top diagram shows the evolution of τ . The response of the 10000 spiking neurons is shown as a raster plot of spike activity. A black point in this diagram indicates a spike of a specific neuron at a specific time in the simulation. The bottom diagram presents the evolution of the membrane potential of a single neuron from the network (green curve) along with its firing threshold θ (red curve). Output spikes of the neuron are indicated as black vertical lines in the same diagram (from [38]).

4.2 A Neuro-genetic Model of a Neuron

The GRN module has several GRNs, each controlling parameters of respective functional area of the NeuCube. The question how to relate the genes from a GRN to the parameters of the spiking neurons that control their spiking activity is to be addressed.

In our realisation here we use the neurogenetic model as an extension of the LIF and the probabilistic neuronal model. Here, instead of using two types of synapses – inhibitory and excitatory as it is in almost all SNN models, we use the proposed in [36,3] four types of synapses for *fast excitation*, *fast inhibition*, *slow excitation*, and *slow inhibition*. The contribution of each to the PSP of the neurons in the NeuCube is defined by the level of expression of different genes/proteins along with the presented external stimuli. The model utilises known information about how proteins and genes affect the spiking activities of a neuron. Table 1 shows what proteins affect each of the four types of synapses in our neurogenetic model. For a real case application, apart from the GABAB receptor some other metabotropic and other receptors could be also included. This information is used to calculate the contribution of each of the *four* different synapses, connected to a neuron n_i , to its post synaptic potential $PSP_i(t)$:

$$\varepsilon_{ij}^{synapse}(s) = A^{synapse} \left(\exp \left(-\frac{s}{\tau_{synapse}^{decay}} \right) - \exp \left(-\frac{s}{\tau_{synapse}^{rise}} \right) \right)$$

where: $\tau_{decay/rise}^{synapse}$ are time constants representing the rise and fall of an individual synaptic PSP; A is the PSP's amplitude; $\varepsilon_{ij}^{synapse}$ represents the type of activity of the synapse between neuron j and neuron i that can be measured and modelled separately for a fast excitation, fast inhibition, slow excitation, and slow inhibition (it is affected by different genes/proteins). External inputs can also be added to model background noise, background oscillations or environmental information.

The genes that relate to the parameters of the neurons are also related to the activity of other genes, forming a GRN. A GRN defines the dynamic interactions between genes/proteins over time that affect the spiking activity of the neuron. Although biologically plausible, a GRN model is only a highly simplified general model that does not necessarily take into account the exact chemical and molecular interactions. A GRN model is defined by:

- (a) a set of genes/proteins, $G = (g_1, g_2, \dots, g_k)$;
- (b) an initial state of the level of expression of the genes/proteins $G(t=0)$;
- (c) an initial state of a connection matrix $L = (L_{11}, \dots, L_{kk})$, where each element L_{ij} defines the known level of interaction (if any) between genes/proteins g_j and g_i ;
- (d) activation functions f_i for each gene/protein g_i from G . This function defines the gene/protein expression value at time $(t+1)$ depending on the current values $G(t)$, $L(t)$ and some external information $E(t)$: $g_i(t+1) = f_i(G(t), L(t), E(t))$.

Table 1. Neuronal action potential parameters and related proteins and ion channels in the computational neuro-genetic model of a spiking neuron: AMPAR - (amino- methylisoxazole- propionic acid) AMPA receptor; NMDR - (N-methyl-D-aspartate acid) NMDA receptor; GABA_AR - (gamma-aminobutyric acid) GABA_A receptor, GABA_BR - GABA_B receptor; SCN - sodium voltage-gated channel, KCN - kalium (potassium) voltage-gated channel; CLC - chloride channel (from [3, 36]))

Different types of action potential of a spiking neuron	Related neurotransmitters and ion channels
Fast excitation PSP	AMPAR [25]
Slow excitation PSP	NMDAR
Fast inhibition PSP	GABA _A R
Slow inhibition PSP	GABA _B R
Modulation of PSP	mGluR
Firing threshold	Ion channels SCN, KCN, CLC

The neurogenetic model of a neuron is a further extension of the probabilistic model from section 3 that is our generic model for the NueCube architecture with the following features: LIF type activity; four different synapses regulated by genes from a GRN; three probabilistic parameters attached to the connections, to the synaptic activities and the activation threshold respectively.

4.3 Optimisation of the GRN Model and the NeuCube Parameters

A major problem with the NeuCube architecture from fig.5 is how to optimize the numerous parameters of the model. Several evolutionary computation methods have been developed for this purpose by our team: PSO [44]; quantum inspired genetic algorithm [11,54,56]; quantum inspired PSO [47,53]. The quantum inspired evolutionary methods can deal with a very large dimensional space as each quantum-bit chromosome represents the whole space, each point to certain probability [35,39]. Such algorithms are faster and lead to a close solution to the global optimum in a very short time. We will be using same parameter values (same GRN) for all neurons in a functional area of the NeuCube. That will result in a significant reduction of the parameters to be optimized. This can be interpreted as ‘average’ parameter value for the neurons in the same area.

When defining parameters of the NeuCube, prior knowledge about the association of spiking parameters with relevant genes/proteins (neuro-transmitter, neuro-receptor, ion channel, neuro-modulator) as described in [37] can be also used.

5 Brain SSTD Modelling and Pattern Recognition

5.1 EEG-, fMRI-, and Integrated EEG + fMRI Pattern Recognition

Recorded brain signals (EEG, fMRI, combined, other) can be used to build a NeuCube model in the following way:

5.1.1 Training of a NeuCube Architecture

1. The Cube is spatially structured to match the spatial distribution of the EEG-, or fMRI- data, or both.
2. The available data is entered into the NeuCube, so that data is entered into the corresponding neuron (neurons) in the Cube. STDP learning is applied in the NeuCube to establish the connection weights of spatial-temporal patterns of pathway connectivity.
3. The output classification module (control module) is trained to recognize the states of the NeuCube into predefined classes (activate desired control devices).
4. The polychronisation patterns formed in the NeuCube, that correspond to each input data pattern, are analysed for the purpose of understanding the data.

5.1.2 Recall of the Trained NeuCube Architecture on New Data

1. New input data is propagated through the NeuCube after encoding into spike trains, so that data from particular areas of the brain are submitted to corresponding neurons in the NeuCube.
2. Output classification (control) results are recorded.
3. The activity of the NeuCube in terms of polychronisation trajectories are analysed and conclusions are made regarding the new input data and the spatio-temporal connectivity and pathways.

5.1.3 Further Adaptation of the NeuCube Architecture

If new data is available that belongs to some of the existing or new classes, further training of the NeuCube architecture is applied and new output classification (control) neurons are added/evolved and trained in the same way as in procedure 5.1.1.

5.1.4 Using EEG, fMRI and Multimodal Data in one NeuCube Architecture.

The proposed here NeuCube architecture allows for multimodal brain data to be used for training the system. In this respect, EEG and fMRI data along with multimodal (e.g. sound/vision/olfactory) data can be used one after another to train the NeuCube, with the hypothesis that each data set will enhance the learning and recognition of the other, making use of the specific characteristics of each of the data sets, such as precise spatial information (fMRI) and precise temporal information (EEG) are used together.

5.1.5 Applications

EEG pattern recognition [48] can be directed to practical applications, such as: BCI [31]; classification of epilepsy [22] (e.g., using deSNN); robot control through EEG signals [41] and robot navigation [2] (e.g., using SPAN). In case of BCI, one scenario is when a NeuCube architecture can be evolved and dynamically visualized to represent the learning process of a subject. fMRI and combined data can be used to discover spatio-temporal connectivity pathways in the brain under different conditions.

5.2 Neuro-genetic Modelling for Cognitive/Emotional Systems and Brain Diseases

Building artificial cognitive systems, such as robots, that are able to communicate with humans in a human-like way has been a goal for computer scientists for decades now. Cognition is closely related with emotions. Basic emotions are joy, sadness, anger, fear, disgust, surprise, but other human emotions play role in cognition as well (pride, shame, regret, etc.). Gene parameters and gene regulatory network models can be used to help a robot evolve its structure and functionality, where genes represented either parameters of dynamic learning processes of the robot, or parameters that connected dynamically different functional modules of the robot (e.g. see [2,43]).

The proposed here NeuCube architecture would make it possible to model cognition-emotion processes that would further enable us to create more human-like robotic systems. Creating human-like behavior in a cognitive system requires understanding relevant brain processes at different levels of information processing. For example, it is known that human emotions depend on the expression and the dynamic interaction of neuromodulators (serotonin, dopamine, noradrenalin and acetylcholine) and some other relevant genes and proteins (e.g., 5-HTTLRP, DRD4, DAT), that are functionally linked to the spiking activity of the neurons in certain areas of the brain and participate in a GRN. They have wide ranging effects on brain functions and their relationship to emotional states is well established. Noradrenaline is important to arousal and attention mechanisms, acetylcholine has a key role in encoding memory function, dopamine is related to aspects of learning and reward seeking behavior and may signal probable appetitive outcome, whereas serotonin release may inhibit behavior with probable aversive outcome. Reward and punishment are fundamental features of emotional behavior.

The NeuCube architecture can be potentially used to model brain data to enhance the study of the brain in its complexity and different levels of operation related to learning, memory, emotions, cognition, or brain diseases. Based on prior information and available data, different NeuCube architectures can be developed for the study of various brain states, conditions and diseases, including [3,18]: epilepsy [22]; schizophrenia; mental retardation; brain aging and AD [52,37], Parkinson disease; clinical depression.

6 Conclusion and Further Directions

The presented here NeuCube architecture opens opportunities for the development of new generation of brain-like intelligent systems for pattern recognition and for a better understanding of the spatial-temporal connectivity of the brain. Software simulations of different brain data will be conducted in the future, including: EEG pattern recognition and comparing results with previous studies of using reservoir computing [57]; EEG pattern recognition for BCI [41,48]; fMRI pattern recognition and comparison with previous studies [58]. A module for dynamic visualisation of NeuCube polychronisation patterns will be developed along with their interpretation in terms of functional and structural pathways discovered. Potential practical applications would include: neuro-rehabilitation robots [63]; neuro-prosthetics;

control and navigation of wheelchair [10]; cognitive and emotional systems [37]; serious games. Implementing the NeuCube architecture, based on the neurogenetic model of neuron with four types of synapses and probabilistic parameters, as a neuromorphic chip [28-30,17] is a next step in this direction. It will make a large scale of engineering applications of this model possible.

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