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NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data

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ABSTRACT

The brain functions as a spatio-temporal information processing machine. Spatio- and spectro-temporal brain data (STBD) are the most commonly collected data for measuring brain response to external stimuli. An enormous amount of such data has been already collected, including brain structural and functional data under different conditions, molecular and genetic data, in an attempt to make a progress in medicine, health, cognitive science, engineering, education, neuro-economics, Brain–Computer Interfaces (BCI), and games. Yet, there is no *unifying computational framework* to deal with all these types of data in order to better understand this data and the processes that generated it. Standard machine learning techniques only partially succeeded and they were not designed in the first instance to deal with such complex data. Therefore, there is a need for a new paradigm to deal with STBD. This paper reviews some methods of spiking neural networks (SNN) and argues that SNN are suitable for the creation of a unifying computational framework for learning and understanding of various STBD, such as EEG, fMRI, genetic, DTI, MEG, and NIRS, in their integration and interaction. One of the reasons is that SNN use the *same computational principle* that generates STBD, namely spiking information processing. This paper introduces a new SNN architecture, called NeuCube, for the creation of concrete models to map, learn and understand STBD. A NeuCube model is based on a 3D evolving SNN that is an approximate map of structural and functional areas of interest of the brain related to the modeling STBD. Gene information is included optionally in the form of gene regulatory networks (GRN) if this is relevant to the problem and the data. A NeuCube model learns from STBD and creates connections between clusters of neurons that manifest chains (trajectories) of neuronal activity. Once learning is applied, a NeuCube model can reproduce these trajectories, even if only part of the input STBD or the stimuli data is presented, thus acting as an associative memory. The NeuCube framework can be used not only to discover functional pathways from data, but also as a predictive system of brain activities, to predict and possibly, prevent certain events. Analysis of the internal structure of a model after training can reveal important spatio-temporal relationships 'hidden' in the data. NeuCube will allow the integration in one model of various brain data, information and knowledge, related to a single subject (personalized modeling) or to a population of subjects. The use of NeuCube for classification of STBD is illustrated in a case study problem of EEG data. NeuCube models result in a better accuracy of STBD classification than standard machine learning techniques. They are robust to noise (so typical in brain data) and facilitate a better interpretation of the results and understanding of the STBD and the brain conditions under which data was collected. Future directions for the use of SNN for STBD are discussed.

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 a human brain has a range of structural and functional areas that are spatially distributed in a constrained 3D space. When the brain processes information, either triggered by external stimuli, or by inner processes, such as visual, auditory, somatosensory, olfactory, control, emotional, environmental, social, or all of these stimuli together, complex spatio-temporal pathways are activated and patterns are formed across the whole brain. For example, '…the language task involves transfer of stimulus information from the inner ear through the auditory nucleus in the 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)…' (Benuskova & Kasabov, 2007). Many other studies of spatio-temporal pathways in the brain have been conducted, e.g. birdsong learning (Hahnloser, Wang, Nager, & Naie, 2008).

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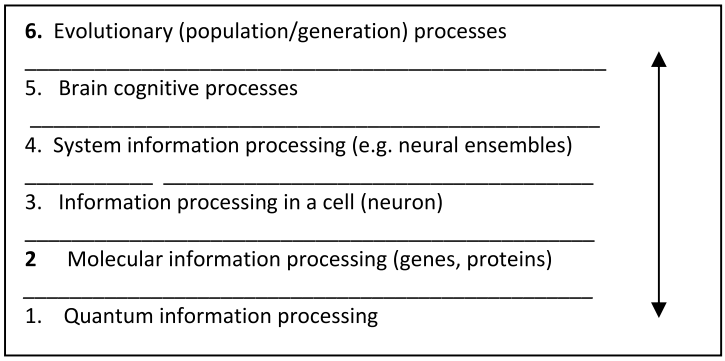

Fig. 1. Different 'levels' of information processing in the brain.
Source: From Kasabov (2007).

In principle, different 'levels' of spatio-temporal information processing can be observed in the brain, e.g. Fig. 1 (Kasabov, 2007), all 'levels' acting in a concert. STBD related to each of these 'levels' can be collected, but how do we integrate this information in a machine learning model?

1.2. Spatio-temporal brain data and brain atlases

Different types of STBD have been collected at the different 'levels' from Fig. 1. At the highest, cognitive level, the most common types are EEG, MEG, fMRI, DTI, NIRS. Electroencephalography (EEG) is the recording of electrical signals from the brain by attaching surface electrodes to the subject's scalp (Craig & Nguyen, 2007; Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007). These electrodes record brain waves which are electrical signals naturally produced by the brain. EEGs allow researchers to track electrical potentials across the surface of the brain and observe changes taking place over a few milliseconds. EEG data is spatio/spectro-temporal in the high frequency spectrum.

Functional MRI (fMRI) combines visualization of the brain anatomy with the dynamic image of brain activity into one comprehensive scan (e.g. Broderson et al., 2011, 2012; De Charms, 2008 and Mitchel et al., 2004). This non-invasive technique measures the ratio of oxygenated to deoxygenated hemoglobin which have different magnetic properties. Active brain areas have higher levels of oxygenated hemoglobin than less active areas. An fMRI scan can produce images of brain activity at the time scale of seconds with precise spatial resolution of about 1–2 mm. Thus, fMRI provides both a 3D anatomical and functional view of the brain in the lower frequency spectrum.

Other methods for whole brain data recording include MEG, DTI (Diffusion Tensor Imaging), single unit electrode data and others (Toga, Thompson, Mori, Amunts, & Zilles, 2006). Magnetoencephalography (MEG) measures millisecond-long changes in magnetic fields created by the brain's electrical currents. MEG machines use a non-invasive, whole-head, 248-channel, *superconducting-quantum-interference-device* (SQUID) to measure small magnetic signals reflecting changes in the electrical signals in the human brain. New methods for brain data collection are being developed and this area of research is likely to be further developed in the future.

Several structural brain atlases have been created to support the study of the brain and to better structure brain data. Probably the first attempt was made by Korbinian Brodmann, who created a cytoarchitectonic map of the human brain, published in 1909. The map presents 43 distinctive areas of the cerebral cortex. Each Brodmann area (BA) is characterized by a distinct type of cells, but it also represents distinct structural area, distinct functional area (e.g. BA17 is the visual cortex), distinct molecular area (e.g. number of neurotransmitter channels) (Zilles & Amunts, 2010). EEG and fMRI data are often mapped into BA for a better interpretation of results (Eickhoff et al., 2005).

An important contribution to the overall brain study and particularly to brain data analysis is the creation of a common coordinate system that can be used for a standardized study of brain data from different subjects and collected by different methods. Talairach and Tournoux (1988) created a co-planar 3D stereotaxic atlas of the human brain (Fig. 2(a)). A software was also made available, called The Talairach Daemon (www.talairach.org) to calculate the Talairach coordinates (x, y, z) of any given point in a brain image along with the corresponding BAs (Fig. 2(b)) (Lancaster et al., 2000).

While the Talairach Atlas was derived from the analysis of a single brain, much further development in stereotaxic mapping was achieved with the introduction of the Montreal Neurological Institute (MNI) coordinates, based on averaged MRI data across individuals, e.g. MNI152, MNI305 (Evans et al., 1993). Mapping of standard brain stereotaxic coordinates was further developed by the International Consortium for Brain Mapping (ICBM) with the release of several brain map templates, such as: ICBM452; ICBM Chinese56; ICBM AD (Alzheimer Disease); MS (multiple sclerosis) and others (Toga et al., 2006). Brain activity measurements, such as EEG and fMRI of any subject can be represented in standard MNI coordinates. MNI coordinates can be translated into Talairach coordinates and Brodmann Areas, and vice versa. The brain gene atlas, discussed further below, contains gene expression data collected from brain areas with identified MNI coordinates. MNI is a common standard now supported by many software systems, e.g. SPM (Ashburner, 2009).

At the lowest 'level' of information processing in the brain (Fig. 1) is the molecular information processing. Spatio-temporal activity in the brain depends on the internal brain structure, on the external stimuli and also very much on the dynamics at gene–protein level. This complex interaction is addressed through computational neurogenetic modeling (Benuskova & Kasabov, 2007). The first issue is how to obtain gene data related to brain structures and functions. The 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 almost 1000 anatomical brain areas of two healthy subjects, 100M data points were collected that indicate gene expressions of several thousand genes and underlie the biochemistry of the sites (Hawrylycz et al., 2012). This is in addition to the previously developed Mouse Brain Atlas.

The enormousness of brain data available and the complexity of the research questions that need answering through integrated models for brain data analysis are grand challenges for the areas of machine learning and information science in general as already pointed in some recent publications (Gerstner, Sprekeler, & Deco, 2012; Koch & Reid, 2012; Poline & Poldrack, 2012; Van Essen et al., 2012).