Mapping, Learning, Visualization, Classification, and Understanding of fMRI Data in the NeuCube Evolving Spatiotemporal Data Machine of Spiking Neural Networks

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***Abstract*— This paper introduces a new methodology for dynamic learning, visualization, and classification of functional magnetic resonance imaging (fMRI) as spatiotemporal brain data. The method is based on an evolving spatiotemporal data machine of evolving spiking neural networks (SNNs) exemplified by the NeuCube architecture [1]. The method consists of several steps: mapping spatial coordinates of fMRI data into a 3-D SNN cube (SNNc) that represents a brain template; input data transformation into trains of spikes; deep, unsupervised learning in the 3-D SNNc of spatiotemporal patterns from data; supervised learning in an evolving SNN classifier; parameter optimization; and 3-D visualization and model interpretation. Two benchmark case study problems and data are used to illustrate the proposed methodology—fMRI data collected from subjects when reading affirmative or negative sentences and another one—on reading a sentence or seeing a picture. The learned connections in the SNNc represent dynamic spatiotemporal relationships derived from the fMRI data. They can reveal new information about the brain functions under different conditions. The proposed methodology allows for the first time to analyze dynamic functional and structural connectivity of a learned SNN model from fMRI data. This can be used for a better understanding of brain activities and also for online generation of appropriate neurofeedback to subjects for improved brain functions. For example, in this paper, tracing the 3-D SNN model connectivity enabled us for the first time to capture prominent brain functional pathways evoked in language comprehension. We found stronger spatiotemporal interaction between left dorsolateral prefrontal cortex and left temporal while reading a negated sentence. This observation is obviously distinguishable from the patterns generated by either reading affirmative sentences or seeing pictures. The proposed NeuCube-based methodology offers also a superior classification accuracy when compared with traditional AI and statistical methods. The created NeuCube-based models of fMRI data are directly and efficiently implementable on high performance and low energy consumption neuromorphic platforms for real-time applications.**

***Index Terms*— Brain data classification, brain data modeling, brain data visualization, evolving spatiotemporal data machines (eSTDMs), functional magnetic resonance imaging (fMRI), NeuCube, neuro information processing, spatiotemporal brain data (STBD), spiking neural networks (SNNs).**

Manuscript received April 11, 2016; revised July 11, 2016; accepted September 8, 2016. Date of publication October 6, 2016; date of current version March 15, 2017. This work was supported by the Knowledge Engineering and Discovery Research Institute of the Auckland University of Technology under an AUT SRIF Grant INTELLECTE 2014–2015.

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Digital Object Identifier 10.1109/TNNLS.2016.2612890

I. Introduction

The human brain processes complex input information across different evoked cognitive states, acting as an ultimate spatiotemporal data processing machine [1]–[5]. For a better understanding of brain dynamics, a proper model is needed to trace this information and the mental processes that generate it. Over the past decades, a variety of techniques have been developed to address this challenge and to analyze spatio/spectrotemporal brain activity. Functional magnetic resonance imaging (fMRI) is a class of neuroimaging methods that measures blood flow changes influenced by neural activities [6]. fMRI uses blood oxygenation level dependence (BOLD) contrast method for observing the level of oxygenation in the blood. fMRI data are rich spatiotemporal brain data (STBD) that represents the localization of neural activity with a high spatial resolution even though with a much lower temporal resolution (i.e., brain activity is measured in time intervals of hundreds of milliseconds). fMRI recording is over time at many, three dimensional small areas represented as voxels. Each of these voxels represents the fluctuation of the BOLD intensity of thousands of neurons over time [6], [7]. fMRI techniques are noninvasive and have been widely used in cognitive science and neuroscience, and in clinical practice and research [8]–[11]. There are numerous common objectives pursued in fMRI data analysis, including: 1) localizing the activated brain regions during a particular mental task; 2) detecting the brain information pathways corresponding to functional activities; and 3) diagnosis or prognosis of disease or psychological states. Many of these tasks have not been solved efficiently with the use of classical machine learning techniques, such as support vector machine (SVM), multilayer perceptron (MLP), and regression techniques [9], [11], the reason being that traditional machine learning techniques are designed to process static vector data and cannot model both interaction and interrelationship between time and space components of STBD, which is needed for the modeling and understanding of fMRI data [1].

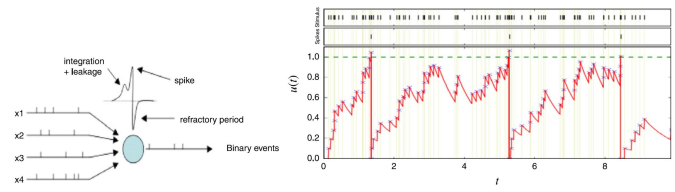
At the same time, the brain-inspired spiking neural network (SNN) models and their neuromorphic highly parallel implementations are advancing very fast [1], [12]–[14], [18]–[25]. The challenge now for information science is to develop new SNN algorithms and methods for efficient learning of STBD (EEG, fMRI, and so on) and for their efficient neuromorphic implementations [1]. In [1] and [22], an SNN architecture is proposed for modeling spatiotemporal data as evolving spatiotemporal data machine (eSTDM), called NeuCube. Here, we introduce a new, generic method for learning, visualization, classification, and interpretation of fMRI data, based on the NeuCube architecture. The method can be applied on any fMRI data across areas of study and applications. We illustrate the method on two benchmark fMRI data sets [15]. The first one is related to modeling, classification, and interpretation of fMRI data measuring person's brain activity when the person is reading affirmative *versus* reading a negative sentence. The second one is related to a mental task of seeing a picture *versus* reading a sentence. The spiking neurons of the NeuCube-based model evolved neuronal connections according to the temporal information "hidden" in the fMRI voxel time series data. This information is visualized in a 3-D SNN cube (SNNc). In Section II, the NeuCube eSTDM is presented and a generic method for fMRI data learning, visualization, and classification based on the NeuCube is introduced. Section III presents the case study problems and data used in this paper and the design of NeuCube-based models to solve these problems. Section IV presents and illustrates the unsupervised learning procedure and model visualization in a 3-D SNNc. Section V describes the classification procedure of fMRI data in the NeuCube-based models and illustrates it on the case study problems. It compares classification results obtained with the proposed models *versus* using standard machine learning techniques. Finally, the conclusions and future work are discussed in Section VI that includes discussing new discoveries form the fMRI data modeling here and future model implementation on neuromorphic hardware platforms [12]–[14].

II. NeuCube SNN Architecture and the Proposed NeuCube-Based Methodology for Learning, Visualization, and Classification of fMRI Data

A. Spiking Neural Networks for Modeling STBD

The brain processes input information in the form of spatiotemporal binary events called *spikes* [16]–[18]. SNN methods have been already developed and implemented as neuromorphic engineering systems, e.g., neuromorphic hardware [12]–[14], SNN for image and speech processing as trains of spikes [19]–[21], unsupervised [23] and supervised learning and classification systems [25]–[27], and so on.

Compared with traditional neuronal networks, SNNs can integrate both spatial and temporal components of data. SNNs are considered the third generation of neural networks [28] and some of their remarkable features are compact representation of space and time, fast data learning, time-based and frequency-based information representation, minimalistic information presentation, and low energy consumption. Due to these reasons, SNN can be considered as suitable models for STBD analysis, such as fMRI data. These features of the SNN are utilized in [1] for the creation of a new type of computational architecture—an eSTDM called NeuCube.



(a) The structure of a LIFM *(b) Functionality of a LIFM*

Fig. 1. Schematic representation of the leaky integrate and fire model (LIFM) of a spiking neuron. (a) Schematic representation. (b) Showing an input train of spikes (top row), the emitted output spikes (second row), and the membrane potential (from [1]).

B. NeuCube

NeuCube is a generic eSTDM based on SNN for learning, classification/regression, visualization, and interpretation of spatiotemporal data, initially proposed for brain data [1]. NeuCube consists of five main modules: data encoding and mapping, unsupervised learning in an SNNc, supervised learning and classification in eSNN, parameter optimization, and model visualization and interpretation. The size of the SNNc is scalable and controlled by three parameters: n_x, n_y, and n_z representing the neuron numbers along the x-, y-, and z-directions. This cube can be used to map the (x, y, z) coordinates of input variables, so that spatial information in the data is preserved. The SNNc is trained in an unsupervised mode on the spike sequences that represent the input spatiotemporal data. After this first phase of training, an eSNN output classifier is trained to learn the SNNc spatiotemporal activities that represent data patterns and their predefined classes. A dynamic evolving SNN (deSNN) can be used as an output classifier [25], but other classifiers can also be employed [24]–[28].

C. Proposed NeuCube-Based Methodology for fMRI Data Mapping, Learning, Visualization, and Classification

The proposed methodology includes the following procedures.

1) fMRI STBD Encoding and Mapping: The input data features (e.g., fMRI voxels) are spatially mapped into spatially allocated spiking neurons in a 3-D SNNc according to the spatial location of these features as brain coordinates. An SNNc is created as a 3-D SNN structure of a suitable size that maps spatially a brain template (such as Talairach [33] and MNI [34]) or voxel coordinates of individual brain data. Then, continuous value time series of voxel data that measure activity at a certain brain location is encoded into a spike train using threshold-based representation (TBR) method or other methods [19], [22], [24]. The timing of the spikes

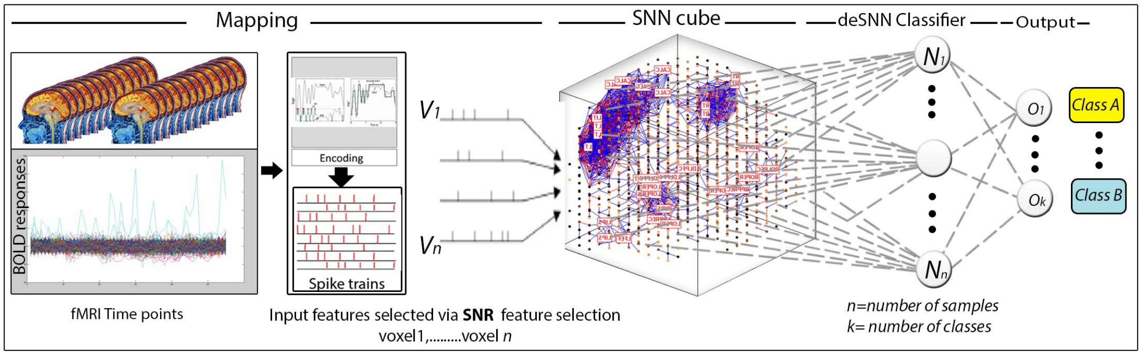


Fig. 2. Schematic representation of the NeuCube-based methodology for fMRI data mapping, learning, visualization, and classification.

corresponds to the time of the changes in the data. A spike time sequence, obtained after the encoding process, represents a new input information to the SNNc where the time unit maybe different from the real time of the data acquisition (machine computation time *versus* data acquisition time). The SNNc can be implemented using the popular leaky-integrate and fire neuronal model (LIFM) (Fig. 1) or other SNN models [29].

The neuronal postsynaptic potential, also called membrane potential $u(t)$, increases with every input spike at a time t, multiplied by 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. The membrane potential can have certain leakage between spikes, which is defined by a temporal parameter τ.

2) Deep, Unsupervised Learning of fMRI Data in an SNNc: The connectivity of the SNNc is initialized using the "small-world" connectivity rule [1], [30], [44]. The small world connectivity rule is phenomenon observed in biological systems [31], [32]. Unsupervised learning is performed using spike-timing-dependent plasticity (STDP) learning rule [23] as one implementation. In this paper, the unsupervised learning allows for the SNNc to evolve its connections, so that they capture spatiotemporal associations between voxels representing consecutive spatiotemporal brain activities. For every input spatiotemporal fMRI sample, a trajectory of connections is formed in the SNNc. The length (the depth) of these trajectories depends on the spiking sequence representing the sample and the time of presentation.

3) Supervised Learning and Classification: An output classification module for supervised learning of spatiotemporal spike sequences, activated in the SNNc by the input data, is implemented using the deSNN classification algorithm [25]. During the supervised learning, output neurons are evolved and trained to recognize whole patterns of activities of the SNNc. A whole pattern of SNNc activity is defined as the spatiotemporal spiking activity of the SNNc during the time of the presentation of a whole input data sample labeled by a class label. The duration of the fMRI samples used can vary in time and number of voxels used. The use of eSNN allows for a further adaptation of the NeuCube model on new data in an incremental way without retraining the model on old data. The model can be further evolved, with new samples used for training and new classes introduced in an incremental way.

4) Parameter Optimization: The output classification accuracy depends on the combination of NeuCube model parameter values. This combination can be optimized using different algorithms, such as grid search (exhaustive search), genetic algorithm, and quantum inspired evolutionary algorithm [24]. A number of default parameters are listed in Section III.

5) Model Visualization and Interpretation: The trained NeuCube model of fMRI data can be dynamically visualized in a 3-D virtual reality space for the analysis of brain activities and for the discovery of new spatiotemporal causal relationships from the data [22].

Here, the proposed NeuCube-based methodology for mapping, learning, and classification of fMRI data is shown graphically in Fig. 2. Section III explains the details of the procedures of the proposed methodology with the use of benchmark fMRI data sets.

III. Case Study Problems on fMRI Data and the Design of NeuCube-Based Models

The STAR/PLUS fMRI data set, originally collected by Marcel Just and his colleagues at the Carnegie Mellon University's Center for Cognitive Brain Imaging [15], [35], was selected for the illustration of the proposed methodology. STAR/PLUS fMRI data sets consist of sequences of images from the whole brain volume captured every 500 ms during a cognitive task. For each subject conducting a picture *versus* sentence task, data from 40 trials have been collected, each trial starting by presenting a stimulus (picture or sentence) that remains on the screen for 4 s (eight brain images recorded). Then, a blank screen appears for another 4 s. After that, the next stimulus is presented for the next 4 s. The fMRI data are spatially partitioned into 27 distinct regions of interest (ROIs), each corresponding to different number of voxels. From the STAR/PLUS fMRI data, two different subsets were extracted and used for two case studies illustrating our methodology. The first data set relates to modeling fMRI STBD when subjects are reading affirmative *versus* negative sentences. The second data set relates to modeling fMRI STBD when a subject is seeing a picture *versus* reading a sentence. In order to analyze and classify voxel activity patterns generated by different stimuli types (picture/sentence), the fMRI data are divided into two classes (first—a subject is seeing a picture and second—

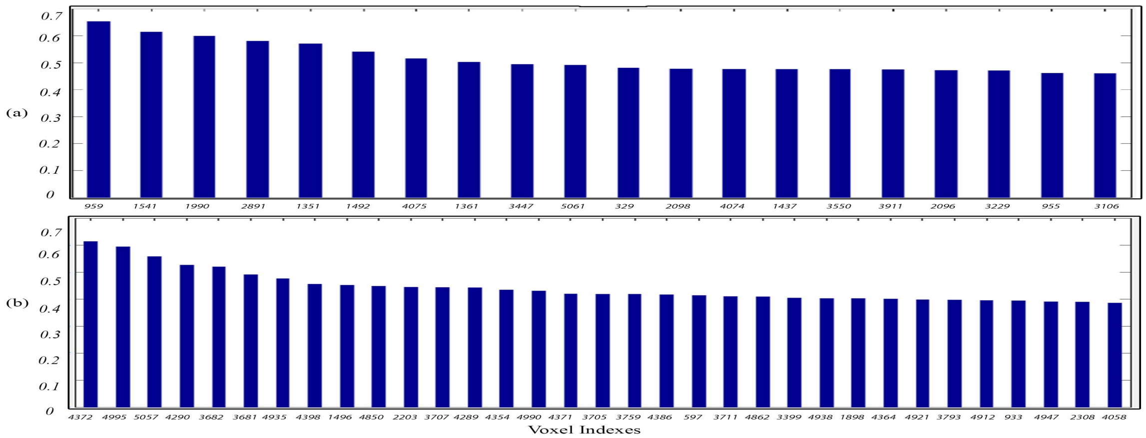


Fig. 3. SNR index (on the y-axis) of top voxels (on the x-axis) extracted from (a) affirmative versus negative sentence fMRI data set and (b) picture versus sentence fMRI data set.

TABLE I

SUBSET OF VOXELS IS SELECTED *via* SNR FEATURE SELECTION METHOD FROM TWO fMRI DATA SETS

Activated brain regions in the Affirmative *vs* Negative sentence task and the number of voxels selected in Fig.3a that belong to each of these regions.	Activated brain regions in the Picture *vs* Sentence task and the number of voxels selected in Fig.3b that belong to each of these regions.
'LT'(3), 'LOPER' (3), 'LIPL'(1)', LDLPFC'(6), 'RT'(2), 'CALC' (1), 'LSGA'(1), 'RDLPFC'(1), 'RSGA' (1), 'RIT'(1)	'CALC' (5), 'ROPER' (3), 'LT ' (4), 'LOPER' (3), 'LSPL' (1), 'RIPS' (3), 'LPPREC' (1), 'RT' (4), 'LFEF' (1), 'LDLPFC' (3), 'RDLPFC'(1) 'LIPS' (2), 'RPPREC' (1), ‘LIT’(1)

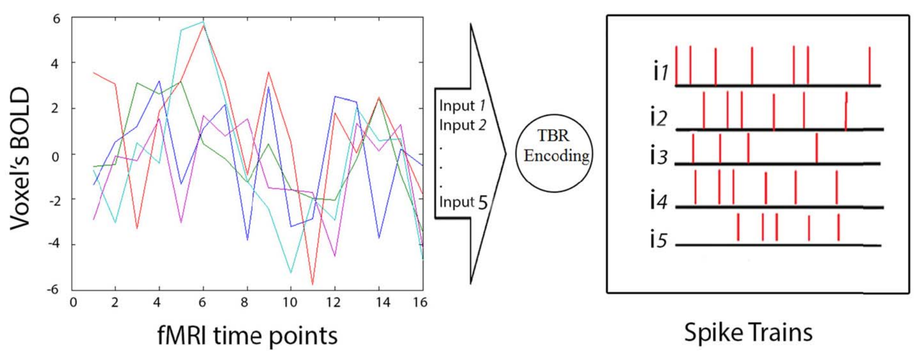


Fig. 4. Example of encoding five voxel time series captured during 8 s (16 brain images) into trains of spikes.

a subject is reading a sentence). We will demonstrate in Sections III–V that using the proposed methodology, we can not only classify these activities, but obtain a better understanding of their spatiotemporal manifestation in the brain.

A. Voxel Feature Selection From the fMRI Data

To analyze the voxel activity patterns of the activated ROIs, either all voxels can be used and mapped in an SNNc model or a suitable subset of voxels can be selected. Different methods for feature selection can be used for the purpose. In our experiments, we have used a standard statistical measure known as signal-to-noise ratio (SNR) [26] via available online NeuCom platform [36]. For a two-class problem, an SNR index for a variable x is calculated as an absolute value of the difference between the mean value $M1x$ of the variable for class 1 and the mean $M2x$ of the variable for class 2, divided to the sum of the respective standard deviations. Fig. 3 shows a set of selected voxels from the fMRI data for each of the two case studies, while Table I shows how many of these voxels belong to which ROI. We conclude from Table I (left column) that when a subject is making a decision about sentence polarity, more activated voxels are located on the left dorsolateral prefrontal cortex (LDLPFC), left temporal (LT), LOPER, and the inferior parietal lobule. Table I (right column) contains the selected voxels while the subject deals with picture/sentence stimuli. Calcarine (CALC) is more activated than the other parts of the brain.

B. Encoding fMRI Data Into Spike Sequences

TBR method was applied on each voxel time series data to transfer the data into a sequence of spikes. If a voxel BOLD intensity value exceeds the TBR threshold, a spike occurs [22]. Fig. 4 shows an example of five voxel time series.

C. Spatial Mapping of fMRI Voxels Into a 3-D SNNc Structure

Here, we have illustrated two types of voxel coordinate mappings in a 3-D SNNc structure: 1) direct mapping of individual fMRI voxel coordinates and 2) mapping fMRI voxel coordinates first into a standard brain template,

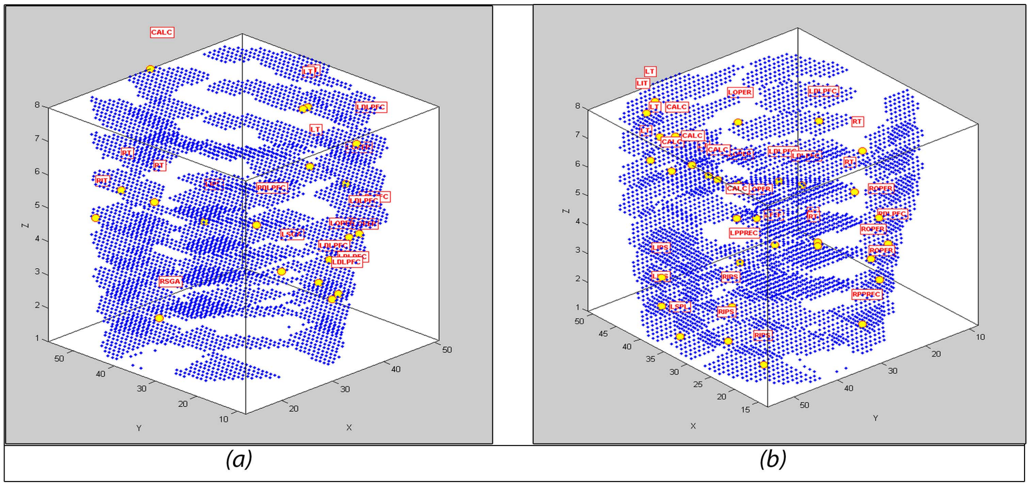


Fig. 5. Direct mapping of voxels into an SNNc. The dimensions of the SNNc are defined by the maximum values of x, y, and z voxel coordinates, which in this case study equal to $51 \times 56 \times 8$. In this dimensional space, 5062 voxels are mapped from the STAR/PLUS geometric voxel coordinates of a single person. The selected voxels in Fig. 3 for each case study problem are shown as input variables as circles, along with the ROI (as text in boxes) for (a) affirmative *versus* negative sentence fMRI data and (b) picture *versus* sentence fMRI data.

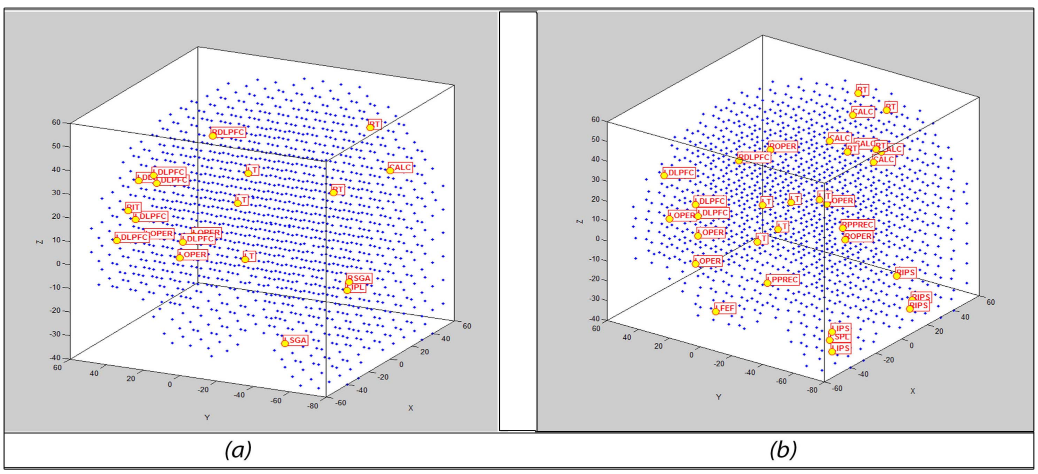


Fig. 6. Mapping voxels into SNNc using the Talairach brain template. The 5062 voxel data of one subject were first mapped into 1471 Talairach template coordinates according to [1], [33], and [38]. Then, each template coordinate is mapped into a corresponding neuron from an SNNc. The selected top informative voxels in Fig. 3 for each case study problem are used as input variables and shown as circles along with the ROI (as text in boxes) for (a) affirmative *versus* negative sentence fMRI data and (b) picture *versus* sentence fMRI data.

such as Talairach [33], and then mapping the Talairach coordinates into a 3-D SNNc. The two methods are shown in Figs. 5 and 6 correspondingly and explained in the following.

1) Direct Mapping of Individual fMRI Coordinates Into a 3-D SNNc: We have used the fMRI data of subject "*05680*" from the STAR/PLUS fMRI data. The fMRI data dimensions are defined by the maximum value of x, y, and z voxel coordinates, which equal in our case study data to $51 \times 56 \times 8$ as can be seen in Fig. 5. Using these dimensions, 5062 voxel coordinates are recorded from the entire brain volume. We mapped all voxel coordinates into an SNNc, so that the spiking neurons have the same 3-D coordinates as the corresponding voxels. Fig. 5(a) shows the spatial mapping of all fMRI voxels into an SNNc. Twenty of these neurons are allocated and labeled to represent input features as per the selection in Fig. 3(a). Fig. 5(b) represents the same brain structure with different preselected voxels for the picture versus sentence data set for the same subject.

2) Mapping fMRI Coordinates to a Standard Brain Template (Talairach) and Then Mapping the Template Coordinates Into an SNNc: When we create a model of fMRI data collected from many subjects, we need to use a unifying structural brain template, such as the Talairach atlas [33], the MNI atlas [34], or other [37]. In this paper, we transformed the coordinates of the preselected voxels and mapped them into a NeuCube of 1471 spiking neurons according the Talairach brain template. Each of these neurons represents the center coordinate of one cubic centimeter area from the 3-D Talairach atlas [38].

In this experiment, for every voxel from an fMRI data set, we calculate the nearest Talairach-based coordinate in the relevant Brodmann area. After mapping the coordinates of the preselected voxels to the Talairach-based coordinates, every voxel is mapped into a spiking neuron in the SNNc according to its new, Talairach transformed coordinates (shown in Fig. 6).

D. Model Parameter Setting

A NeuCube model performance is highly sensitive to parameter setting. Some of the most important parameters are as follows.

1) *TBR_{thr}:* A self-adaptive bidirectional threshold for STBD encoding to spike trains.
2) *D_{thr}:* Distance threshold for the initialization of the neuronal connectivity in the used here small world connectivity rule.
3) *STDP Learning Rate (α):* A parameter used to modify the neuronal connections in an SNNc with respect to repetitively arrived spikes to the synapses. If a neuron i fires before a neuron j, then its connection weight increases, otherwise it decreases with respect to the STDP learning rate (α).
4) *Th_o:* Threshold of firing for the neurons in the SNNc.
5) *deSNN Classifier Parameters:* These parameters are: *mod* and *drift*. As explained in [1] and [25], an output neuron is evolved for every training sample and connected to all neurons of the SNNc. The weight initialization of every new connection is based on the RO learning rule [39]. The weight is calculated as a modulation factor (the variable mod) to the power of the order of the incoming spikes. The initial connection weights are further modified to reflect the following spikes, using a *drift* parameter [25]. Once the structure of the NeuCube-model is defined, along with the method for data encoding and the method for voxel spatial mapping into a 3-D SNNc, the model is trained and analyzed. These steps are illustrated in Sections IV–V.

IV. Deep, Unsupevised Learning in a 3-D SNNc, Connectivity Visualization, and Analysis

After a NeuCube model is defined, the SNNc is trained with the encoded fMRI data using the STDP method [23]. A whole spatiotemporal pattern of a known class is used as one sample. Depending on the method used for mapping the fMRI voxels (features) into the SNNc, different aspects of the fMRI data can be revealed and studied during the SNNc training as explained in the following. Experimental results are illustrated here mainly to enable visual exploration of the models, but numerical analysis is also facilitated in NeuCube, where numerical and statistical data about connection weights, spiking intensity, and time of activation, are obtained from the model and analyzed (see the NeuCube software—www.kedri.aut.ac.nz/neucube/). The main aspect of this type of learning in the SNNc is that the length of the spatio-temporal patterns used as single samples is not limited and the learning is as deep as it needs to be, restricted only by the number of the neurons in the SNNc which can be made large enough during initialization of the Cube.

A. Learning and Visualization of Spatiotemporal Connections in the SNNc With the Use of the Talairach Template Mapping

1) Case Study of Affirmative Versus Negative Sentence: Fig. 7 shows the initial connections in the SNNc and the modified ones after the deep, unsupervised learning process using both affirmative and negative sentence fMRI samples.

Our findings confirm studies that suggest that language comprehension, including a reading task, is processed in particular brain areas, such as LDLPFC, Broca, and Wernicke [40]. Fig. 7 shows more and stronger neuronal connections generated in the left hemisphere. These connections were established as a result of more spikes transferred between the neurons located in these areas, reflecting on the changes in the corresponding voxels in the fMRI data. Fig. 8 shows connectivity after the SNNc was trained with only the affirmative or the negative sentence data, separately. The observed connectivity from Fig. 8 confirms that the subject performs differently when reading an affirmative *versus* negative sentence and also suggests what the difference is in terms of brain spatiotemporal activity.

In addition, we can observe that more and stronger connections are formed between neurons located in the left hemisphere (LDLPFC and LT) than in the right hemisphere (RDLPFC and RT) while the subject was reading a negative sentence. The connectivity is especially enhanced between the input neurons (i.e., the selected voxels) located in the LDLPFC and LOPER regions. Our interpretation of Fig. 8 is in line with the neuroscience literature, which reported that comprehension of negative sentences is cognitively different from affirmative sentences, involving different parts of the brain. Containing negative words, such as "not," in the middle of a sentence can make it more difficult to comprehend, due to their more complex syntactic and semantic structures. Therefore, this type of sentence engages more regions of the brain [41], as shown in Fig. 8. More detailed analysis on the connectivity related to the task can be performed by neuroscientists to answer different research questions.

Another form of analysis of a trained SNNc is clustering of the neurons that can be performed with the use of the input variables (corresponding neurons) used as cluster centers. Each neuron in a trained SNNc belongs to the cluster from which center it has received most spikes, as shown in Fig. 9. A spreading algorithm [42] was used to define these clusters. If there are more transmitted spikes between two neurons, there will be a stronger information route between them. Fig. 9 shows the SNNc clusters after unsupervised training of an SNNc with the two fMRI time series separately. Fig. 9(a) shows that there are not many functional pathways between LT region and the other parts of the brain while the subject is reading an affirmative sentence. However, Fig. 9(b) shows that when a subject is reading a negative sentence, there is more interaction between neurons located in the left hemisphere. Therefore, more brain functional paths start from the input voxels located in the LT region (spike sender neuron) and continue up to the neurons located in the middle of the brain (spike receiver neurons).

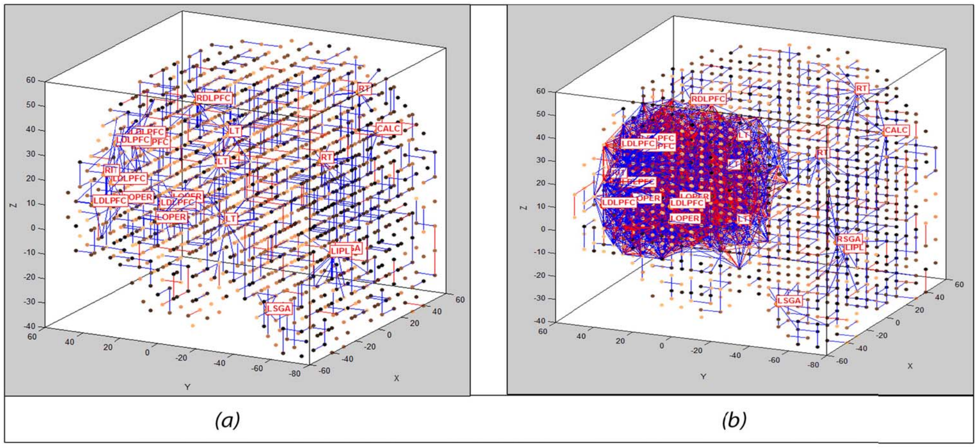


Fig. 7. Voxels are mapped into SNNc using Talairach template. (a) Initial connections in an SNNc. (b) Learned connections after STDP unsupervised learning using both affirmative and negative sentence fMRI samples when 20 input voxels selected as in Fig. 3. The dense areas of connectivity evolved in the SNNc can be analyzed to understand the most active functional areas in the brain during these two tasks and how they interact dynamically.

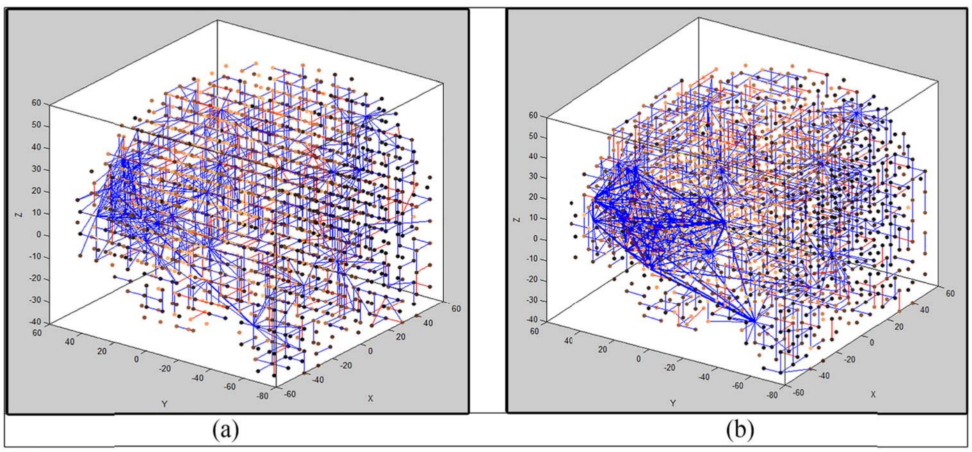


Fig. 8. Voxels are mapped into SNNc using Talairach template. (a) Learned connections in an SNNc when only fMRI samples of affirmative sentences were used. (b) Learned connections in an SNNc when only fMRI samples of negative sentences were used. The initialization is the same as in Fig. 7. The dense areas of connectivity evolved in the SNNc can be analyzed to understand the difference between functional areas in the brain during each of the two tasks as dynamic interaction.

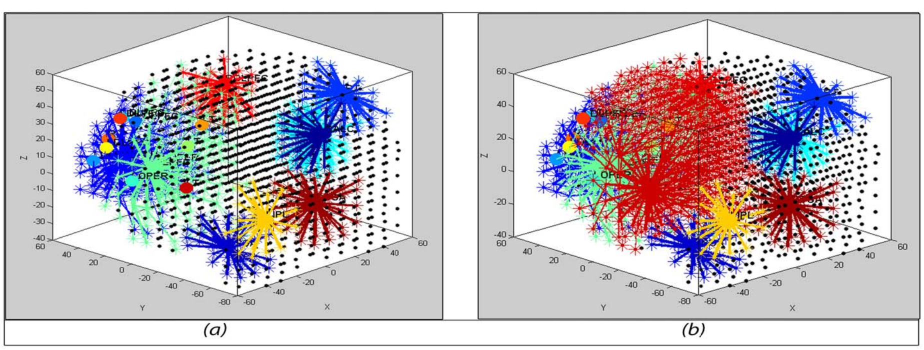


Fig. 9. Voxels are mapped into SNNc using Talairach template. Clustering of neurons in an SNNc after unsupervised training for (a) affirmative sentence data and (b) negative sentence data. The size of a cluster indicates the importance of the input feature/voxel at the center of the cluster. This can be used for feature/voxel selection and marker identification for further studies.

2) Case Study of Learning Picture Versus Sentence Data: Similar to Fig. 7 and the experiments in Section IV-A1, here, Fig. 10 shows the learned connections in an SNNc using the samples of seeing a picture [Fig. 10(a)] and reading a sentence [Fig. 10(b)], while Fig. 10(c) and (d) shows a 2-D projection of the connectivity from Fig. 10(a) and (b) correspondingly.

Visual perception initiates as soon as the eye transfers light to the retina, where it is absorbed by a layer of photoreceptor cells. The outputs of the retina then pass through the optic nerve, cross, and split at the optic chiasm, through the optic tract to the lateral geniculate nucleus. From there, they pass to primary visual cortex [43]. After training the SNNc with the fMRI samples of seeing a picture, Fig. 10(a) and (c)

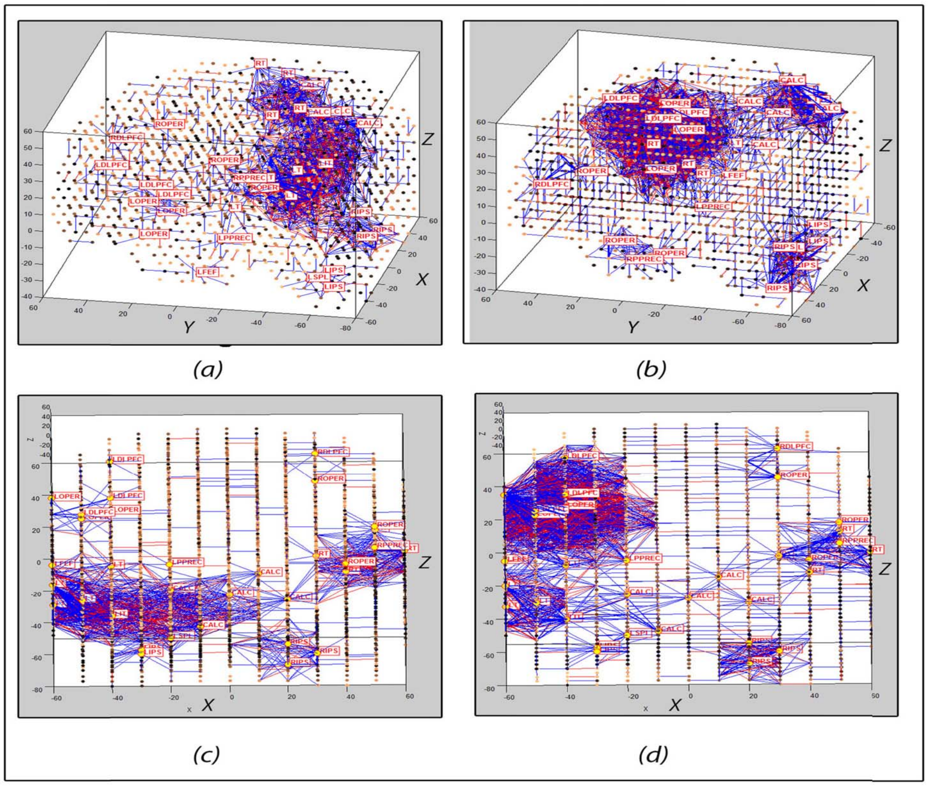


Fig. 10. Voxels are mapped into SNNc using Talairach template. (a) Connectivity of an SNNc trained on fMRI data related to seeing a picture. (b) Connectivity of an SNNc trained on fMRI data related to reading a sentence. (c) 2-D projection of the connectivity of the SNNc from Fig. 10(a). (d) 2-D projection of the SNNc from Fig. 10(b). The dense areas of connectivity evolved in the SNNc can be analyzed to understand the difference between functional areas in the brain during each of the two tasks as dynamic interaction.

represents a stronger spatiotemporal interaction between neurons located in the parts of the brain dedicated to vision, such as CALC region, which is located in the primary visual cortex in the occipital lobe and defined as the Brodmann area 17. This result confirms our previous argument that the visual primary cortex is more activated than the other parts of the brain when the subject is performing a visual task (seeing a picture). On the other hand, as shown in Fig. 10(b) and (d), when the SNNc is trained with spike sequences that represent fMRI data related to sentence stimulus, more number of neuronal connections are created in the left hemisphere, in particularly, in Broca, and Wernicke areas. This corresponds to the studies about brain areas involved in language comprehension. Using the NeuCube model, a more detailed analysis can be conducted in terms of understanding the dynamic patterns of brain activities represented as connectivity evolution in time.

3) Learning and Visualization of Spatiotemporal Connections in a Trained SNNc Using Direct Voxel Mapping: In order to visualize the neural connectivity and spiking activity inside an SNNc with 5062 spiking neurons for example (equal to the number of voxels in the STAR/PLUS fMRI data of an individual), we have loaded the whole fMRI voxel coordinates into the SNNc, as explained in Section III. Fig. 11 shows the neuronal connections before and after unsupervised training of an SNNc with the use of four different data sets, related correspondingly to affirmative sentence, negative sentence, seeing a picture, and reading a sentence.

It is seen from this visualization that the exact locations of the fMRI voxels are mapped in the same 3-D location of spatial located neurons. These neurons develop their connections based on the temporal information in the fMRI data during the STDP learning. As seen in Figs. 8 and 10, the neuronal connections in the SNNc here evolved differently during the unsupervised training of the SNNc with fMRI data related to reading a sentence *versus* seeing a picture, reflecting the different evoked cognitive functions in the brain.

As shown in Fig. 11, we obtained similar results by training an SNNc with the same fMRI data samples, but through different SNNc mappings. More and stronger neuronal connections were generated between the neurons located in the left hemisphere, significantly in the LDLPFC area, when reading negative sentences. Visual areas were more activated when seeing a picture. These results represent the NeuCube-based SNNc stability to generate similar outputs for the same input spike trains, while using different brain templates for fMRI voxel mapping. Using standard brain templates, such as Talairach, MNI, and so on, to map fMRI data into an SNNc model allows the creation of a model from data collected from multiple subjects. In contrast, a direct fMRI voxel mapping would allow for a single person model creation that can be used for a personalized modeling and a better understanding of a single individual brain activity during a cognitive task.

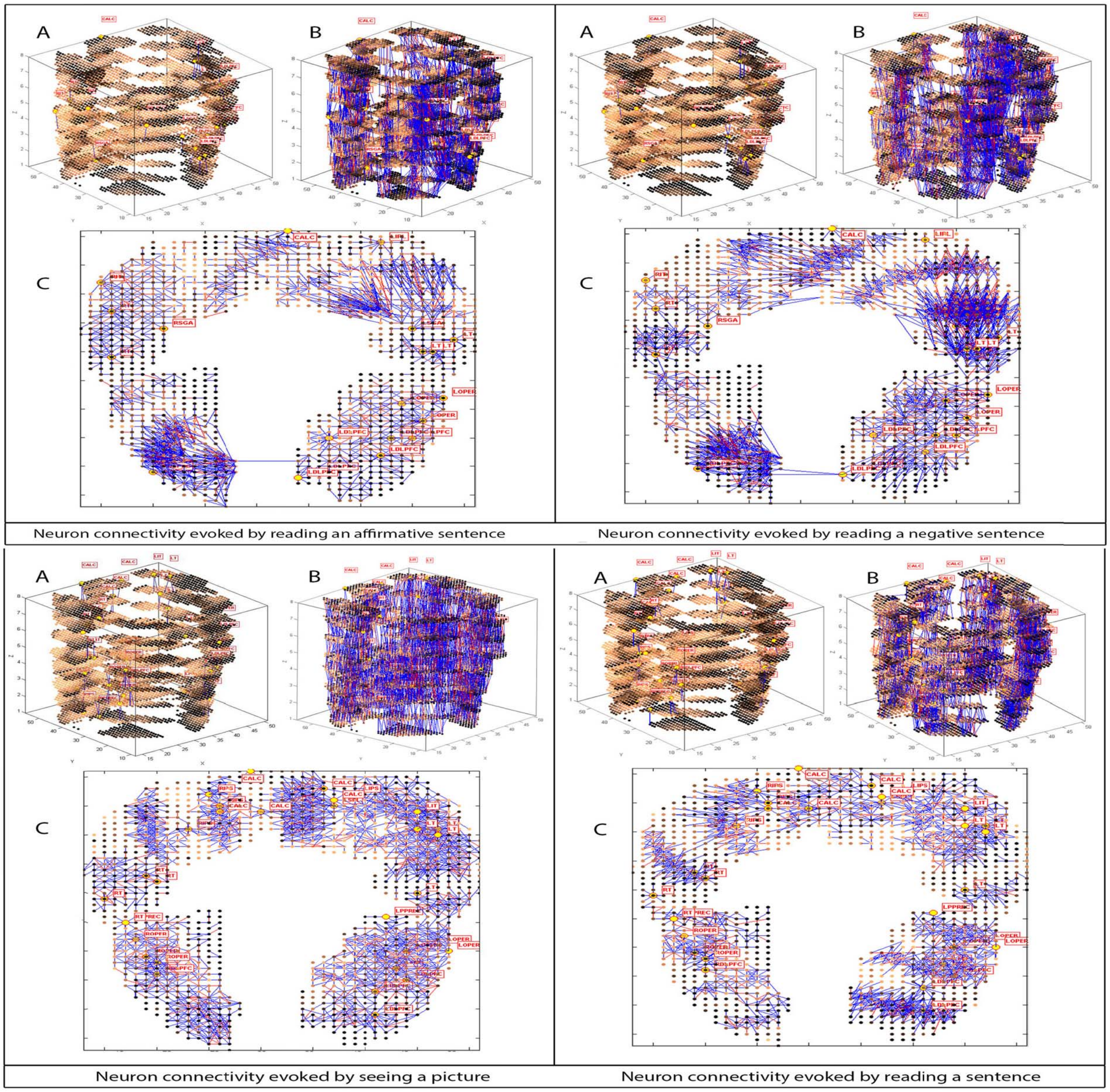


Fig. 11. Voxels are directly mapped into an SNNc model. Initial (A) and final (B) connectivity of an SNNc after training with four different data sets, related correspondingly to affirmative sentence, negative sentence, seeing a picture, and reading a sentence. The final connectivity is also shown as a 2-D projection (C). Positive connections are shown in blue and negative connections are shown in red.

To reveal more information about interrelation between voxel activities, clustering of the spiking neurons in a trained SNNc can be performed using the same method as in Section IV-A (see also Fig. 9). This is shown in Figs. 12 and 13. Here, spiking neurons represent voxels rather than Talairach coordinates as it is the case in Fig. 9. A comparison of Fig. 12(c) and (d) shows that more brain information routes are generated while reading a negative sentence. In fact, more cognitive states of the brain are evoked to understand a sentence syntax and semantics. The unlabeled black dots represent those neurons that did not receive spikes. Fig. 13(c) and (d) shows the spiking activity clusters in the SNNc model trained on subject data when seeing a picture and reading a sentence, respectively.

V. fMRI Data Classification in a NeuCube Model Using Dynamic Evolving SNN Classifier

A. Classification of fMRI Data in a NeuCube-Based Model

While the SNNc learns fMRI data and creates spatiotemporal patterns of connectivity and spiking activity among spiking neurons, the output classifier is to classify these patterns into predefined class labels [1], [25]. After completion of the unsupervised learning in the SNNc, input data is propagated again through the now trained SNNc in order to activate the learned patterns in the SNNc, so that a classifier can be trained to classify them. For every training sample, a new output neuron is evolved and connected to all neurons in the SNNc. Here, we have used the deSNN classifier [25]. It is constructed

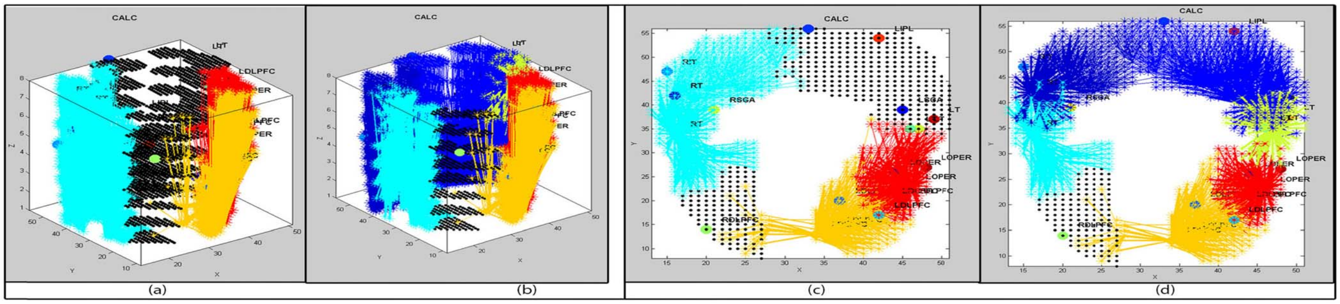


Fig. 12. Voxels are directly mapped into an SNNc model. Clustering of the neurons in a trained SNNc with (a) affirmative sentence data and (b) negative sentence data, along with their corresponding 2-D projections shown in (c) and (d), correspondingly. The size of clusters indicates the importance of the feature voxel for the task and can be used for feature/voxel selection for further studies.

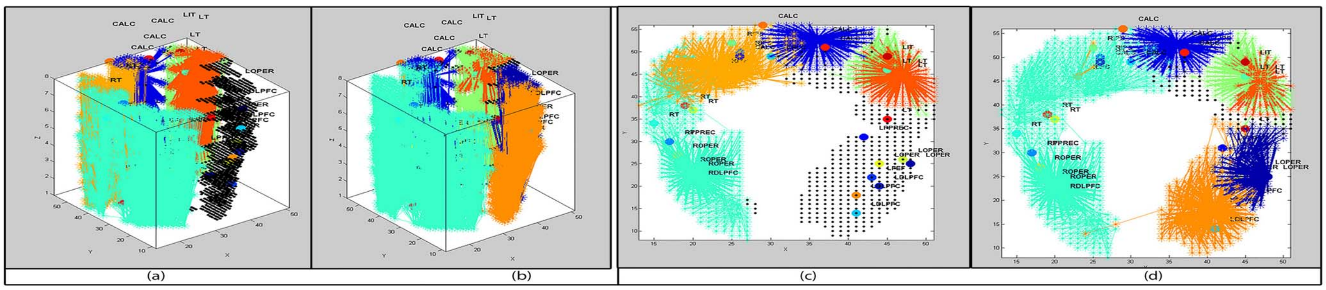


Fig. 13. Voxels are directly mapped into an SNNc model. Clustering of the neurons in a trained SNNc with (a) fMRI data related to seeing a picture and (b) fMRI data related to reading a sentence, along with their 2-D projections shown in (c) and (d), correspondingly. The size of the clusters indicates the importance of the features (voxels) for the task and can be used for feature/voxel selection for further studies.

TABLE II

OPTIMAL PARAMETER SETTINGS OF NEUCUBE-BASED MODELS FOR DIFFERENT EXPERIMENTS (SESSIONS) WITH THE BENCHMARK fMRI DATA

Optimised parameters for the tow classification tasks:	Experiment (Session) – see Tables III and IV	TBR threshold for the encoding procedure	Connection distance (small-world radius)	STDP learning rate	SNN firing threshold in the SNNc	deSNN parameter - *mod*
Affirmative vs. negative sentence data set	Session I	3.327	0.128	0.010	0.5	0.4
	Session II	2.852	0.125	0.013	0.5	0.4
	Session III	2.0929	0.108	0.014	0.5	0.4
Picture vs. sentence data set	Session I	4.355	0.125	0.006	0.5	0.4

and trained to learn and classify different trajectories of the SNNc spiking activities that represent different input patterns from the fMRI data that belong to different classes. As a result of the supervised learning in the classifier, once a new fMRI data sample of unknown class is entered, the classifier will classify this data into a known class, or will create a new class.

The deSNN classifier belongs to the class of evolving systems [26], so that it can incrementally add new samples and new classes with no need to retrain it with the old data and without manifesting the catastrophic forgetting phenomenon. The deSNN utilizes a combination of rank-order learning [39] for the establishment of the initial weights of the synapses based on the order of the first arriving spike, and STDP-type learning for the tuning of these weights based on the following spikes arriving at the synapse.

B. NeuCube Model Parameter Optimization and Classification Results for the Benchmark Data Sets

In a NeuCube fMRI model, the output classification accuracy depends on the parameter setting. In the experiments here, a grid search method was used, where for different combinations of parameter values (in our experiment 10 000), a model is created and its classification accuracy evaluated. Optimal parameter values of a model that are resulting in best classification accuracy are reported in Table II.

Table III summarizes the fMRI data classification accuracy of the affirmative sentence class *versus* negative sentence class obtained using the NeuCube-based classification model. The results are compared with results obtained using traditional machine learning methods, as these methods are still being actively used in the literature for the purpose of classification of STBD. The methods used for comparison are SVM, multiple linear regression, MLP, evolving classification function, and evolving clustering method (see www.theneucom.com). The already published classification result of the affirmative *versus* negative sentence fMRI data [9] is also reported. The NeuCube-based models achieved significantly better classification accuracy (Table IV). In addition to a better classification results, the visualization of the trained SNNc reveals new information about functional brain pathways.

In both experiments, the fMRI data were learned in the NeuCube models as whole spatiotemporal patterns. In contrast,

TABLE III

CLASSIFICATION ACCURACY OF THE AFFIRMATIVE SENTENCE (CLASS C1) *Versus* NEGATIVE SENTENCE (CLASS C2) DATA *via* A NeuCube MODEL (50% OF THE DATA USED FOR TRAINING AND 50% USED FOR TESTING AS CROSS VALIDATION) AND ALSO TRADITIONAL MACHINE LEARNING METHODS (OBTAINED *via* NeuCom, www.theneucom.com), ALONG WITH ALREADY PUBLISHED RESULTS [9]. THE fMRI DATA SAMPLE FILE CONTAINS 40 SAMPLES (20 SAMPLES PER CLASS)

Method	Sessions and selected voxels for classification	C1 (affirm)	C2 (negat)	Total
NeuCube	*Session I:* 20 voxels selected from TABLE I (left column)	**80%**	**100%**	**90%**
	Session II: 20 pre-selected voxels from RDLPFC region	**90%**	**80%**	**85%**
	Session III: 20 pre-selected voxels from LDLPFC region	**90%**	**80%**	**85%**
SVM results obtained in [9]	*Session I:* classification based on the LDLPFC's voxels	64%	68%	66%
	Session II: classification based on the RDLPFC's voxels	65%	69%	67%
	Parameter setting for traditional machine learning methods			
SVM	SVM Kernal: Polynomial, Degree, Gamma, N/A : 1	70%	75%	73%
MLP	Number of Hidden Units=180, Number of Training Cycles=600, Output Activation Function- linear.	75%	65%	70%
ECF	Maximum Field Radius=1, Minimum Field Radius= 0.01; M of N=3; Number of Membership Functions= 2; Number of Epochs= 4	55 %	70%	63%
ECMC	Maximum Field Radius=2; Minimum Field Radius=0.01, M of N=3	65%	70%	70%
MLR	Class Performance Variance=0.26	65%	60%	63%

TABLE IV

COMPARISON OF CLASSIFICATION ACCURACY OF PICTURE (CLASS C1) VERSUS SENTENCE (CLASS C2) DATA OBTAINED BY USING NeuCube (50% OF THE DATA USED FOR TRAINING AND 50% USED FOR TESTING IN A CROSS VALIDATION MODE) AND TRADITIONAL MACHINE LEARNING METHODS (OBTAINED VIA NeuCom, www.theneucom.com). THE EXPERIMENT IS DONE ON A TOTAL NUMBER OF 80 SAMPLES (40 SAMPLES PER CLASS)

Classification accuracy results from NeuCube-based model		Accuracy		
Method	Session and selected voxels for classification	C1 (pict)	C2 (sent)	Total
NeuCube	*Session I:* 33 voxels selected from TABLE I (right column)	**85%**	**90%**	**87.5%**
Classification results from traditional machine learning methods				
SVM	Parameter setting			
	SVM Kernal: Polynomial, Degree , Gamma, N/A:1	85%	85%	85%
MLP	Number of Hidden Units: 304, Number of Training Cycles: 300 Output Activation Function: linear	75%	77%	76%
ECF	Maximum Field R.= 2, Minimum Field R.= 0.01; M of N= 3 Number of Membership Functions= 2; Number of Epochs= 4	77%	80%	78%
ECMC	Maximum Field R.=1;Minimum Field R.=0.01; M of N= 3	82%	72%	77%
MLR	Class Performance Variance: 0.13	75%	62%	68%

the same fMRI data were learned in the other methods a vector-based, where vectors were formed through concatenating of temporal frames. No dynamic spatiotemporal fMRI patterns can be revealed while using these methods.

VI. CONCLUSION AND DISCUSSION

In this paper, we proposed a new, generic methodology for mapping, learning, visualization, classification, and understanding of fMRI data using the NeuCube architecture of SNN [1]. The methodology includes procedures for feature selection from fMRI data, spatial mapping of the data and the features into a 3-D SNN structure SNNc, unsupervised learning in the SNNc, visualization of the connectivity and the spiking activity of the trained SNNc for the discovery of new information and knowledge related to the data and the brain processes that generated it, supervised learning in an SNN classifier, parameter selection and optimization, and model validation. In this respect, a solution to a problem defined by fMRI data is not a single formula or an algorithm, but an eSTDM that consists of several modules, each of them having a set of alternative algorithms and parameter values that can be optimized. To illustrate the proposed methodology, we have used part of the benchmark STAR/PLUS fMRI data that records the activities in an evoked area of the brain while a human subject was reading a sentence or seeing a picture. We also analyzed the voxel activity patterns generated by reading an affirmative sentence versus a negative sentence. We have used a NeuCube evolving SNN model to classify the voxel activity patterns into predefined classes. As feature selection, a subset of voxels was selected using SNR feature selection [26]. These informative voxels were used as features to train an SNNc and to classify the data.

In all experiments, the NeuCube-based models were superior in two aspects when compared with traditional machine learning methods: 1) they can be interpreted in terms of understanding dynamic interactions between functional areas of the brain during a cognitive task, either for many subjects, or for an individual subject; none of the traditional methods (reported in Tables III and IV) can be interpreted in such a way and 2) a higher classification accuracy is achieved.

Experimental results are illustrated here mainly to illustrate how the proposed method enables visual exploration of the models. Numerical analysis is also facilitated in NeuCube, where numerical and statistical data about connection weights, spiking intensity, time of activation, and so on can be obtained from the model and analyzed (NeuCube software is available at www.kedri.aut.ac.nz/neucube/).

The experimental results proved our hypotheses that the following holds.

1) The proposed NeuCube-based methodology is superior in fMRI data learning and classification when compared with traditional statistical and AI methods, as the NeuCube learns whole spatiotemporal patterns from the data.
2) NeuCube learns fMRI data in an incremental, adaptive way, where new data and new classes can be added.
3) As only one-pass learning is used in a NeuCube model, online learning for real time applications is also supported.
4) The learned connections in the SNNc represent valid dynamic spatiotemporal relationships derived from the fMRI data that can be interpreted for the discovery and understanding of new functional information about the brain. The observations from the analysis of the NeuCube models correspond to the known information from the brain theory [43]. A NeuCube model can be further interpreted for finding new spatiotemporal information. For example, we can not only visually observe in a trained SNNc that the left hemisphere was more activated than the right hemisphere when reading a negative sentence, but discover the dynamics in the activation of these areas through tracing the evolving connectivity over time. We can not only observe that the spatiotemporal connections between the neurons in the visual primary cortex were stronger than the connectivity in the LDLPFC, which was more activated while the subject was seeing a picture, but zooming on particular areas of the connections in a trained SNNc would also reveal more information about the spatiotemporal brain processes related to the tasks and would allow neuroscientists to answer different research questions.

VII. Future Directions

Future work includes the use of other SNN classifiers or spike-pattern associators, such as tempotron, ReSuMe, and SPAN [24]. As a NeuCube-based model uses a classifier to classify SNNc activities that capture meaningful spatiotemporal patterns from data, our research question in the future will be what patterns can be captured in the classifiers. A NeuCube model is a special type of a liquid state machine (LSM) [28] that has new features of learning, spatial variable mapping, model visualization, and so on that make a NeuCube model meaningful in terms of its interpretation for the sake of understanding of spatiotemporal characteristics of the data. The proposed NeuCube models are scalable in terms of dimensionality of an SNNc that can map with a high precision large scale fMRI data of tens and hundreds of thousands of voxels. As a NeuCube simulator is available in PyNN, along with Java and MATLAB [22], this makes it possible for a direct implementation of an fMRI model on many available neuromorphic hardware platforms [12]–[14], [18]–[21], [44] for fast processing of large volumes of fMRI data in an online, real time mode. Computational platforms, such as SpiNNaker [12] and TrueNorth [13], along with hybrid neuromorphic chips [14] of thousands and millions of spiking neurons with a very low energy consumption can now be used for fMRI data. In this respect, the proposed method is the first to enable a direct use of neuromorphic hardware for a meaningful fMRI data modeling and analysis.

Overall, this paper offers a principally new and efficient neuromorphic approach to better model and understand one of the most used and most complex STBD and fMRI data. It is a method for learning spatiotemporal patterns of dynamic changes across the learned variables (in this case—voxels). The proposed method explores for the first time the use of SNN for this purpose. The visualization and interpretation of the learned connections suggest dynamic, functional spatiotemporal associations between measured areas of the brain represented by voxels in relation to the task performed. Potential applications of the proposed methodology span across all brain cognitive and medical studies. It will boost the development of neuromorphic supercomputing hardware platforms, showing how they can be efficiently used for large fMRI data modeling in a real time.

Acknowledgment

The authors would like to thank E. Capecci and J. D'Mello who helped with the preparation of this paper. They are indebted to the Reviewers, the Associate Editor, and the Editor-in-Chief for their detailed, precise, and constructive comments and suggestions that helped them tremendously. A NeuCube software version is available free at: http://www.kedri.aut.ac.nz/neucube/.

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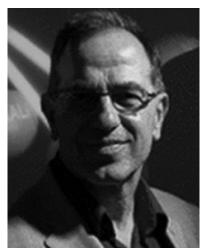

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