A Spiking Neural Network Methodology and System for Learning and Comparative Analysis of EEG Data From Healthy Versus Addiction Treated Versus Addiction Not Treated Subjects

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Abstract—This paper introduces a method utilizing spiking neural networks (SNN) for learning, classification, and comparative analysis of brain data. As a case study, the method was applied to electroencephalography (EEG) data collected during a GO/NOGO cognitive task performed by untreated opiate addicts, those undergoing methadone maintenance treatment (MMT) for opiate dependence and a healthy control group. Methods: the method is based on an SNN architecture called NeuCube, trained on spatiotemporal EEG data. Objective: NeuCube was used to classify EEG data across subject groups and across GO versus NOGO trials, but also facilitated a deeper comparative analysis of the dynamic brain processes. Results: This analysis results in a better understanding of human brain functioning across subject groups when performing a cognitive task. In terms of the EEG data classification, a NeuCube model obtained better results (the maximum obtained accuracy: 90.91%) when compared with traditional statistical and artificial intelligence methods (the maximum obtained accuracy: 50.55%). Significance: more importantly, new information about the effects of MMT on cognitive brain functions is revealed through the analysis of the SNN model connectivity and its dynamics. Conclusion: this paper presented a new method for EEG data modeling and revealed new knowledge on brain functions associated with mental activity which is different from the brain activity observed in a resting state of the same subjects.

Index Terms—Electroencephalography (EEG) comparative analysis, EEG data, EEG data classification, evolving spiking neural networks (eSNNs), GO/NOGO tasks, methadone maintenance treatment (MMT), NeuCube, opiate addicts, spatiotemporal brain data (STBD).

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I. INTRODUCTION

HE human brain can be considered a complex system that processes input information through the interaction of around hundred billion neurons. The brain data are transferred between these neurons in the form of binary events called spikes. Every neuron transfers and receives chemicals, such as potassium, chloride ions and sodium, and produces electrical current. These signals can be recorded as spatiotemporal brain data (STBD). Over the past decades, a variety of techniques have been developed to capture STBD when the human brain is activated by a cognitive task. Electroencephalography (EEG) is one of the techniques that records brain cortical activity via electrodes that are attached to the head [1]. EEG captures STBD with high temporal resolution is able to detect changes of cortical activities that occur in milliseconds. Therefore, EEG is a direct measure of the neurocortical dynamic changes associated with perception and cognitive function, such as memory and attention. Over the last four decades, EEG has been used extensively for brain studies including addiction research. It is recognized as a sensitive measure of drug effects on the brain, which often manifest as changes in the size and time course of the postsynaptic potentials [2] that are reflected in alterations in EEG activity. It has also been shown that reinforcing effects of many drugs mediated by the mesolimbic dopamine pathway modify EEG recordings [3]. EEG data analysis is a complex task and a range of methods and applications for interpreting this data have been applied including using artificial neural networks for classification, activation detection, etc. EEG data contains both spatial and temporal components, and a challenge for information science and artificial intelligence is to develop new algorithms and methods for efficient processing of STBD.

Recently, the brain-inspired spiking neural network (SNN) models and their neuromorphic highly parallel implementations have been advancing very fast [4], [5], as is also argued in [6]. In contrast to the traditional statistical analysis, a new framework called NeuCube has been successfully shown to be a rich platform for the STBD analysis [7], [8].

In this paper, we present a novel methodology, based on the NeuCube architecture [6] for learning, modeling, classification, and comparative analysis of EEG data recorded during a GO/NOGO cognitive task. Making use of the proposed method, we aimed to investigate the patterns of EEG activity elicited

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from three groups of human subjects: 1) patients undertaking methadone maintenance treatment (MMT) for opiate dependence; 2) active opiate users without substitute treatment; and 3) healthy volunteers. We also visualized the neuronal connectivity generated in a 3-D brain-like SNN cube (SNNc) to display the spatiotemporal differences between spikes emitted by neurons against the EEG patterns generated by different groups of subjects completing different cognitive tasks. The overall aim of the study was to extend our understanding of drug-related effects on cognitive functions along with a presenting a novel method for EEG data analysis.

This paper is organized as follows: Section II describes the GO/NOGO task—a frequently used cognitive task that generates a dynamic spatiotemporal pattern of brain activity across many areas of the brain. Section III describes the NeuCube framework [6] and discusses how this framework is used as a generic methodology for EEG data classification, modeling, and analysis. Section IV describes an application of this methodology on an EEG case study data and demonstrates how this framework might be used to assist the understanding of drugrelated cognitive effects. The final section provides conclusion and suggestions for future research.

II. COMPLEX DYNAMIC BRAIN ACTIVITIES DURING THE GO/NOGO TASK

The ability to successfully inhibit thought, behavior, and the response to irrelevant stimuli is crucial for the proper functioning of many other cognitive capacities, such as learning, decision making, and potentially affects an individual's functioning in daily life, e.g., safely crossing a busy road [9]. The GO/NOGO task has been used for several decades as a measure of the executive functions of the prefrontal cortex, in particular the ability to inhibit inappropriate automated responses. During a GO/NOGO task, a participant is required to perform an action given certain stimuli (e.g., press a button-GO) and inhibit that action under a different set of stimuli (e.g., not press that same button-NOGO). Typically, NOGO stimuli are rare and task instructions are to execute a fast GO response. Therefore, there is increased conflict when the NOGO stimulus is presented. Although the GO/NOGO task appears simple, requiring a response according to a conditional rule, it reflects high-level cognitive functions including decision making, response selection, and inhibition. Evidence shows that groups characterized by clinically relevant impulsivity, e.g., drug users, tend to show diminished inhibition of responses to NOGO stimuli, thus making more errors of commission [10].

Brain dynamic changes in the GO/NOGO task have been widely investigated using EEG recordings. In this paper, we present the potential for using the SNN model for the analysis of EEG data that measure complex dynamic brain activity during the GO/NOGO task across healthy subjects and subjects under drug treatment. The use of SNN is of crucial importance, especially their ability to learn dynamic spatiotemporal patterns in a NeuCube organized architecture [6].

III. PROPOSED SNN NEUCUBE-BASED METHOD FOR STBD LEARNING, CLASSIFICATION, AND COMPARATIVE ANALYSIS

A. SNNs and the NeuCube Framework

SNN models are inspired by a biologically realistic model of the brain that processes dynamic input information across a large number of spiking neurons. SNN are considered the third generation of neural networks with potential to solve complex STBD through evolving computation [11]. In SNN models, in addition to the neurons' synaptic states, the time component is also incorporated in their operations. Every neuron in the SNN model can be implemented using the Leaky-Integrate and Fire Model of a spiking neuron [6].

In order to facilitate a SNN learning process, connection weights between neurons are modified by transferring spikes across synapses. Many methods for SNN have been already created: Encoding continuous data, such as image and speech data, into trains of spikes [12]–[14]; spatiotemporal data learning [11], [15], [16]; SNN reservoir computing and liquid state machines (LSMs) [17], [18]; classification systems [19], [20].

Based on SNN, methods and systems have been developed and applied for audio–visual information processing [20]; STBD modeling [6]; brain–computer interfaces [21]; moving object recognition [22]; cognitive data modeling [8]; finite automata modeling [23]; personalized prediction systems [24], etc.

Some of the remarkable features of SNN are: compact representation of space and time; fast data learning; and time-based and frequency-based information representation. For these reasons, SNN can be considered a suitable technique for STBD analysis, such as EEG, fMRI [7], [8], etc. These features of the SNN are used in [6] for the creation of a new type of computational architecture—a spatiotemporal machine called NeuCube that is a brain-inspired evolving spiking neural network (eSNN) architecture for STBD learning, modeling, knowledge extraction, and the analysis of the brain processes that generated the data [6], [19], [22], [25].

B. The NeuCube Framework

The NeuCube SNN architecture consists of several modules: STBD encoding and mapping; unsupervised learning in an SNNc; supervised learning and classification; and parameter optimization.

1) Module 1—NeuCube Encoding and Mapping:

a) STBD Encoding: STBD signals are transformed into temporal spike trains using a threshold-based representation (TBR) method [13]. The generated spike trains represent changes in the STBD that exceeded a threshold TBR_{thr}.

b) STBD Mapping: Regarding the STBD mapping, a 3-D brain-like SNNc is created to map the spatial components of STBD. SNNc is scalable in size, i.e., it is adaptable to any number of neurons to map different brain templates (e.g., Talairach, MNI, etc. [26]). After mapping the brain template, input neurons are allocated in SNNc to transfer the spike trains. In order to preserve the spatial information, each allocated input neuron has the same (x, y, z) coordinates with the corresponding variables' coordinate in the used brain template.

c) SNNc Initialization: Neurons in SNNc are initially connected together using the *small-world* connectivity rule [6]. Each neuron in the SNNc is connected to its nearby neurons which are within a distance threshold $D_{\rm thr}$. These connections are later modified based on the learning of new incoming spikes [6] during the unsupervised learning stage.

2) Module 2—Unsupervised Learning and SNNc Visualization: After mapping the spatial components to the SNNc, we train the SNNc with the input spike sequences using the spiketiming-dependent plasticity (STDP) learning rule [15], which is used in an unsupervised learning phase. STDP adjusts the connection weights between the neurons based on the relative timing of a particular neuron's output and input spikes. Therefore, the STDP learning process encodes the "hidden" spatiotemporal relations between STBD variables in the form of neuronal connections and spiking activities in the SNNc.

3) Module 3—Supervised Training and Classification: The second training phase is performed using dynamic evolving spike neural networks [22], which trains the output classifier based on the association between class labels and training samples. The same data that has been used for the unsupervised training phase is propagated to the SNNc to train the output neurons of the classifier. At this step, for each training sample, an output neuron is dynamically created and connected to all neurons of the SNNc. The initial connection weight W_{ij} between a neuron n_i and a neuron n_j is set to zero and later modified depending on the order of the first arrived spike from n_i to n_j and a modulation factor (mod) as

$$W_{ij} = \operatorname{mod}^{\operatorname{order}(i,j)}.$$
(1)

The classification results can be evaluated using random subsampling cross validation (RRSV) or leave-one-out cross validation (LOOCV).

4) Module 4—Parameter Optimization: A NeuCube model is a stochastic model (i.e., initial connections between the neurons in the SNNc are randomly generated using small world connectivity). The output classification accuracy depends on the parameter settings. In order to optimize the classification accuracy results, modules 1–3 are repeated using different Neu-Cube parameter settings to obtain the best results. The best classification as well as the optimal parameters can be saved and reported. A number of prime parameters of the NeuCube are listed as follows:

- TBR_{thr}: A self-adaptive bidirectional threshold for STBD encoding to spike trains;
- $D_{\rm thr}$: Distance threshold for the neuron connectivity in small world connectivity rule;
- STDP learning rate (α): A parameter to modify the neuronal connections with respect to repetitive 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).
- (Th_o): Threshold of firing is used to represent the firing state of the output neurons in classifier;

- *Mod:* According to the rank-order learning [22], connection weight between neuron i to neuron j is computed depending on a modulation factor mod and the order of the first incoming spike, order (i, j), as mentioned previously in (1).
- *Drift*: To modify the initial connection weights, the occurrence of following spikes is taken into account with respect to time. If there is a spike arriving from neuron *i* at time *t* after the first one was emitted, then the weight increases by drift value, otherwise it decreases.

C. Proposed SNN NeuCube-Based Method for EEG Data Learning, Classification, and Comparative Analysis

Owing to the advantages of the SNN model and the interpretability of the 3-D SNNc, successful NeuCube models have been developed across cognitive and other applications [24], [25], [27]. Fig. 1 depicts the proposed NeuCube based method of EEG modeling, classification, and pattern recognition on the case study of GO/NOGO task performed by different groups of subjects.

Fig. 1 (top row) represents brain processes captured as EEG data during a cognitive GO/NOGO task. Then the EEG signals are encoded to spike trains using the TBR or an other method. Fig. 1 (middle row) shows the mapping of the EEG data variables to the SNNc, which contains 1471 spiking neurons, each representing 1 cm³ brain area according to the Talairach atlas. Also, for each EEG channel, one input neuron is allocated to transfer the spike trains to the SNNc. After mapping the SNNc, the cube is trained using temporal components of the data (spike trains). During the unsupervised STDP learning (module 2), the spatiotemporal spike trains, that represent the EEG STBD, are transformed into neuronal connections. These connections capture repetitive spatiotemporal patterns from the EEG data.

The learned connections can be observed, visualized, and analyzed for a better understanding of the data and for comparative analysis across EEG data from different subject groups. The transparent structure of the SNNc and its spatial organization, that maps spatially the brain data allows tracing changes in the connections in a step-wise manner in response to the EEG spike input sequences. The evolution of SNNc connectivity throughout the learning process is illustrated in Fig. 2. Fig. 2 shows that starting with small random connections (initialized SNNc), the SNNc created new connections over time, reflecting the spatiotemporal relationships in the EEG data.

IV. ACTIVITY EEG STBD CLASSIFICATION AND COMPARATIVE ANALYSIS OF GO/NOGO TASK PERFORMED BY HEALTHY-, ADDICTION TREATED-, AND ADDICTION NOT TREATED SUBJECTS

A. Case Study Problem Specification

Methadone has been used as a pharmacological substitute for the treatment of opiate dependence since the mid-1960s. The benefits of MMT have been demonstrated by many studies. For example, MMT has been shown to effectively reduce the use of other drugs, injection-related risky behavior, criminal



Fig. 1. Block diagram of the NeuCube modules for EEG data encoding, mapping, visualization, learning, and classification. The mapping module illustrates the allocation of 26 EEG channels as 26 input neurons in an SNNc of 1471 neurons. The initial spatiotemporal connections between the spiking neurons in the SNNc are created with the use of the small-world connectivity before unsupervised training is applied.



Fig. 2. Dynamic visualization of the evolution of neuronal connectivity and spiking activity in a SNNc of 1471 spiking neurons with Talairach-based coordinates [26]. (a), (b) Step-wise neuronal connectivity and spiking patterns of the SNNc at two steps during a SNNc unsupervised learning. The blue lines are positive (excitatory) connections, while the red lines are negative (inhibitory) connections. The brighter the color of a neuron, the stronger is its activity. Thickness of the lines identifies neuronal-enhanced connectivity.

activity, mortality, transmission of HIV, and other blood-borne pathogens, such as hepatitis-B [28]–[30].

MMT is now the most common treatment for opiate dependence in many countries, including the United States of American (USA), Australia, the United Kingdom (U.K.), and New Zealand (NZ). Despite methadone's effective clinical use, it remains uncertain whether MMT has negative effects on some cognitive functions, given methadone has clinically similar actions and analgesic effects to morphine [31]. There is particular concern about whether long-term use of a sedative opiate agonist, such as methadone has effects on cognitive function. One way to address this problem is to measure EEG data during cognitive activities of groups from MMT, opiate, and healthy subjects and to comparatively analyze the results through model creation and model interpretation.

B. Participants

- The MMT group: The group undertaking MMT were recruited following recommendations from the case managers of Auckland Community Alcohol and Drug Services, NZ. The MMT group consisted of 18 males and 14 females, with a mean age of 39.36.
- 2) The Opiate user group (OP): Opiate users were recruited from the Auckland Drug Information Outreach Trust Needle Exchange Services by advertisement. The group included 11 males and 6 females, with a mean age of 37.38.
- 3) The Healthy control group (CO): A group of 21 healthy control subjects was recruited by advertisements in a range of local communities. This group included 14 males and 11 females, with a mean age of 36.12.

C. EEG Data Acquisition

The EEG data was recorded via 26 cephalic sites: Fp1, Fp2, Fz, F3, F4, F7, F8, Cz, C3, C4, FC3, FCz, FC4, T3, T4, T5, T6, Pz, P3, P4, O1, O2, and Oz electrode sites (10–20 International System).

D. GO/NOGO Task

GO/NOGO task is a psychological test to measure a participant's capacity for response control and sustained attention. During the task, the participants were repeatedly presented with the word "PRESS" (for 500 ms). The color of the word "PRESS" was presented randomly in either red or green. Participants were instructed to respond by pressing a button with the index finger of both hands in response to the word that appeared in green (GO) and not respond to the word that appeared in red (NOGO).

Participants were asked to complete the practice trial prior to the real test to ensure that they understood the task. At this stage, the word "PRESS" was presented in the same color six times in a row. There were 28 sequences, 21 of which were presented in green, and 7 in red, presented in a pseudorandom order, with an interstimulus interval of 1 s. The task duration was approximately 5 min. Speed and accuracy of response were stressed equally in the task instructions.

E. Input EEG Data Preparation for the SNN NeuCube Modeling

In this study, the EEG signal patterns of the MMT, OP, and control subjects were used as the input STBD to the SNNc to demonstrate the differentiation between their brain activity patterns against the GO/NOGO task. For this purpose, we extracted several EEG sample files from the recorded EEG data and analyzed them separately using the NeuCube model during the following experimental sessions.

Session I: Six EEG sample files were created separately, each containing EEG data captured from one group (MMT/OP/CO subjects) per cognitive task (GO versus NOGO). Then each sample file was entered separately for training a SNNc and the resulted SNNc were compared to capture the differences between brain activity patterns of each group of participants performing GO vs NOGO.

Session II: In this session, we only considered the EEG data related to the GO trials to compare the brain activity patterns of different groups of subjects against the same cognitive task.

Session III: In this session, we only considered the EEG data related to the NOGO trials as these trials are common interest of studies on response inhibition, we compared the NeuCube models created for each group.

The organization of the data is presented in Table I.

F. Tracing, Interpreting, and Understanding Dynamic Brain Activities During the GO/NOGO Task Performed by the Three Subject Groups of CO, MMT, and OP Through the Connectivity and Spiking Activity Visualization

During the learning process in SNNc, when neuron n_i fires at time t, neurons that are connected to n_i will receive a spike from it and their potentials increase by synaptic weight of the entered spikes. However, the potentials of those neurons that do not receive the spike will leak. Hence, greater transmitted spikes between two neurons lead to stronger connectivity. According to Fig. 3, control subjects exhibited less excitation in NOGO trials when the response must be withheld in comparison with GO trials when the response is required. In contrast, excitations induced during the NOGO trials were much greater than those induced during the GO trials in either MMT or OP subjects. These findings reflect the group differences on brain activity induced by the two competing response tendencies (GO versus NOGO), implicating deficits in inhibition to prevent the execution of the GO response in the subjects with history of opiate dependence no matter what their current treatment status. After the SNNc unsupervised training, neuronal connections with stronger weights reflect more spike transmissions between neurons' synapses. Therefore, the induced brain functional pathways that reveal the connection strength in SNNc, can be visualized. In Fig. 4, we cluster functional communications created through the spiking input data from 5 EEG channels, namely C3, Fz, Cz, C4, and P4. These channels were chosen because of their significant involvement in the human response inhibition. Fig. 4 represents this information for the control, MMT, and OP subjects while they were responding to GO trials versus NOGO trials. The functional pathways of the control subjects [see Fig. 4(a1)] show

TABLE I EEG DATASETS FOR THE THREE EXPERIMENTAL SESSIONS TO COMPARE THE BRAIN ACTIVITY PATTERNS OF THE CONTROL (CO), MMT, AND OPIATE (OP) SUBJECTS IN A GO/NOGO TASK

Classifications	Samples per class	EEG sample file size			
Session I: EEG data sample fi	les for GO versus NOGO classific	ation			
GO Trials class	21 control Subjects	75 EEG time points * 26 channels * 21 samples			
	18 OP subjects	75 EEG time points * 26 channels * 18 samples			
	29 MMT subjects	75 EEG time points * 26 channels * 29 samples			
NOGO Trials class	21 control Subjects	75 EEG time points * 26 channels * 21 samples			
	18 OP subjects	75 EEG time points * 26 channels * 18 samples			
	31 MMT subjects	75 EEG time points * 26 channels * 31 samples			
Session II: EEG data sample f	iles captured during GO trials				
MMT class versus CO class	29 MMT samples (class 1)	75 EEG time points * 26 channels * 50 samples			
	21 control samples (class 2)				
OP class versus CO class	18 Opiate samples (class 1)	75 EEG time points * 26 channels * 39 samples			
	21 control samples (class 2)				
MMT class versus OP class	29 MMT samples (class 1)	75 EEG time points * 26 channels * 47 samples			
	18 Opiate samples (class 2)				
Session III: EEG data sample	files captured during NOGO trials	S			
MMT class versus CO class	31 MMT samples (class 1)	75 EEG time points * 26 channels * 52 samples			
	21 control samples (class 2)				
OP class versus CO class	18 OP samples (class 1)	75 EEG time points * 26 channels * 39 samples			
	21 control samples (class 2)				
MMT class versus OP class	31 MMT samples (class 1)	75 EEG time points * 26 channels * 49 samples			
	18 OP samples (class 2)	1			

that the spatiotemporal relationship was extensively observed in the neurons connected to the allocated input neuron for the Cz channel. By tracing the neuron connections that contain the most number of transmitted spikes, several functional pathways were traced for the Cz channel as a spike sender neuron. Fig. 4(b1) illustrates the brain information pathways captured from the MMT subjects during the GO trials. The spike transition from the Cz was decreased in the MMT subjects in comparison with the Control subjects. On the other hand, the functional pathways generated by Fz channel were increased. Although the brain activity patterns of the Cz and Fz channels appeared differently in MMT and Control subjects, their brain functional pathways were comparable. In contrast, the brain functional pathways of the Opiate subjects were significantly different from either the Control or the MMT subjects indicated by the absence of functional pathways initiated from the Cz channel [see Fig. 4(c1)]. Consistent with our previous studies [32]–[34], these findings indicate the possible abnormality of brain function associated with the long-term exposure to opioid-type drugs. However, patients undertaking MMT for opiate addiction appeared less impaired than those current opiate users.

G. Comparative Analysis of Brain Activities of MMT Subjects Under Different Drug Doses Versus CO and OP Subjects

Members of the MMT group were receiving different doses of methadone. To examine the dose-related effects, the EEG patterns of the MMT subjects were categorized into two groups based on their current methadone dose: High dose (>60 mg/day) and low dose (\leq 60 mg/day). The EEG patterns of these two groups were learned in an SNNc and their functional pathways were visualized. Fig. 4(d) captures the differences between model functional pathways generated by five EEG channels in MMT subjects on low and high methadone dose. The captured model functional pathways of those MMT subjects that used a high dose were more similar to the OP group. On the other hand, the MMT subjects with less amount of methadone dose performed similar functional pathways to the control group. Fig. 5 captures the information spike communication between 26 EEG electrodes after NeuCube unsupervised training. Each vertex represents a neuronal cluster corresponding to an EEG channel and the arcs represent relative spike amounts transmitted between different neuronal clusters. The wider the line between input neurons, the more spikes were transmitted between the corresponding clusters.

In Fig. 5(a), by comparing two graphs obtained from control subjects in GO versus NOGO trials, it is clear that the spike communication was especially enhanced between neuronal clusters while the subjects were performing GO trials. Consequently, we can conclude that less spike interactions were manifested, while subjects increased inhibition of responses during NOGO trials in comparison with GO trials. Perhaps, the green appurtenance of the word "PRESS" helps to strength the visibility to healthy subjects and induces an enhanced activation in the central parietal and occipital areas, which probably encompasses the primary and secondary visual areas.

However, this trend is absent in either the MMT or opiate subjects. Furthermore, both the MMT and opiate subjects demonstrated increased spike communication in a wide range of areas, in particular, in the frontal, central, and temporal areas during the NOGO trials, implicating increased stimulation induced by NOGO stimuli in the areas related to attention, visual memory, and execution of voluntary movements. Our findings suggest anatomically and functionally different inhibition processes between people with history of opiate use and healthy control subjects. It is also noted that alternation of inhibition process are greater in the opiate users compared to the MMT subjects. For opiate subjects in NOGO trials, the majority of the wide lines were created between channel F4 and channels T6, P4, PZ, P3, T5, CP4, T4, C4, and CZ. These connections represented more



Fig. 3. Illustration of the SNNc connectivity after the NeuCube training with EEG data of 26 features (channels) for the experimental GO/NOGO task. The learnt connectivity of the SNNc is different for the control (healthy), MMT, and OP subjects related to the GO vs NOGO task. The blue lines are positive (excitatory) connections, while the red lines are negative (inhibitory) connections. The brighter the color of a neuron, the stronger is its activity with neighboring neurons. Thickness of the lines also identifies the neuron's enhanced connectivity. The 1471 neurons of the brain-like SNNc are spatially mapped according to the Talairach brain atlas [26].

spikes transmitted between neuronal clusters corresponding to the channel F4 and the other neuronal clusters while the subjects were undertaking NOGO trials. Consequently, the ability of the opiate subjects to inhibit their voluntary responses may be impaired during NOGO trials. On the other hand, the interactions between these channels are not observed in the control subjects during NOGO trials. It means that there were not many spikes transmitted between the neuron clusters related to channel FZ and the other EEG channels. In the graph obtained from MMT subjects in NOGO



Fig. 4. Model functional pathways clustered for Control, MMT, and OP subjects generated by five EEG channels (sender spike neurons) and the rest of the neurons inside the SNNc (receiver spike neurons) while doing GO trials versus NOGO trials. The big solid dots represent the input neurons and other neurons that are labeled with * sign are receiver spike neurons. The lines represent the connectivity between neurons. Unconnected dot means no spikes arrived at this neuron. (a1) Model functional pathways of the control subjects in GO trials. (a2) Model functional pathways of the control subjects in NOGO trials. (b1) Model functional pathways of the MMT subjects in OGO trials. (b2) Model functional pathways of the MMT subjects in GO trials. (b2) Model functional pathways of the MMT subjects in C1) Model functional pathways of the OP subjects in GO trials. (c2) Model functional pathways of the OP subjects in GO trials. (d1) Model functional pathways of MMT group that received less than 60 mg methadone dose per day. (d2) Model functional pathways of MMT group that received more than 60 mg methadone dose per day. All figures are rotated and illustrated in 2 views.

trials, there were strong spike communications between FZ, CP4, and T4 clusters, although these connections were less in comparison with opiate subjects. The observed differences in spike communication implicate that the control and Opiate subjects performed differently while they were doing cognitive GO/NOGO tasks.

To achieve a better understanding of the spike occurrence and propagation inside the SNNc, the number of the spikes emitted by each neuron during the unsupervised training is illustrated in Fig. 5(b). While the SNNc was training with EEG data, the postsynaptic potential of each neuron n_i at time t PSPi(t) [35] increased by the sum of the input spikes received from all

Fig. 5. (a) Total interaction between 26 neuronal clusters representing 26 EEG channels in terms of spike communication. The thicker the line that connects two nodes of the graph that represent the corresponding clusters of connected neurons in the SNNc, the more spikes are transmitted between these clusters. (b) Number of spikes emitted by each neuron of the SNNc after SNNc unsupervised training with an exemplar EEG data recorded from Control, MMT, and Opiate subjects in GO versus NOGO trials. The blue lines are the positive spikes (excitatory) emitted by all neurons in the SNNc, while the red lines are negative spikes (inhibitory) emitted only by the input neurons representing the EEG channels.





TABLE II Optimal NeuCube Parameters That Resulted From a Grid Search to Optimize the Classification Accuracy as an Objective Function

Session	EEG sample files used in NeuCube classification	$TBR_{\rm thr}$	D_{thr}	STDP rate
I	Control subjects in Go versus Control subjects in NOGO	0.551	0.150	0.010
	MMT subject in GO versus MMT subject in NOGO	0.949	0.150	0.010
II	OP subjects in GO versus OP subjects in NOGO	0.777	0.150	0.010
	MMT subject versus Control subjects (GO task)	0.463	0.225	0.014
	Opiate subjects versus Control subjects (GO task)	0.450	0.075	0.013
Ш	MMT subject versus Opiate subjects (GO task)	0.669	0.208	0.008
	MMT subjects versus Control subjects (NOGO task)	0.532	0.225	0.006
	Opiate subjects versus Control subjects (NOGO task)	0.468	0.175	0.005
	MMT subjects versus OP subjects (NOGO task)	0.886	0.225	0.014

TABLE III

EEG DATA CLASSIFICATION ACCURACY RESULTS FROM THREE EXPERIMENTAL SESSIONS VIA RRSV METHOD OF THE NEUCUBE

Control subjects (CO), Opiate subjects (OP), Accuracy is reported in %									
Session	Classification	NeuCube	SVM	MLP	MLR	ECMC			
Session I: GO versus NO classification	Control subjects in Go versus NOGO	90.91	50.55	48.50	50.38	29.71			
	MMT subjects in Go versus NOGO	83.87	50.39	49.72	50.17	42.65			
	Opiate subjects in GO versus NOGO	83.33	50.40	47.81	50.00	45.43			
Session II: OP, MMT, CO classification in GO	MMT subject versus Control subjects (GO)	77.00	47.12	45.36	49.86	50.47			
	Opiate subjects versus Control subjects (GO)	85.00	50.50	50.64	48.60	48.60			
	MMT subject versus Opiate subjects	79.00	47.90	45.22	50.53	49.98			
Session III: OP, MMT, CO classification in NOGO	MMT subjects versus Control subjects	85.00	49.13	48.62	50.49	50.15			
	Opiate subjects versus Control subjects	90.00	50.24	49.83	50.24	49.83			
	MMT subjects versus OP subjects	88.00	46.57	50.51	50.00	48.71			

50% of the data was used for training and 50% used for testing. The results of the traditional methods were obtained via LOOCV.

presynaptic neurons. Once the PSPi (t) reaches the firing threshold, neuron n_i emits a spike. After the SNNc unsupervised learning, temporal activities of the spiking neurons can be interpreted in terms of brain activities measured by the corresponding EEG channels.

An example of the number of spikes emitted by every neuron of the SNNc related to the EEG data is given in Fig. 5(b). By comparing the results obtained from GO versus NOGO trials, we can conclude that the average number of emitted spikes in control subjects were greater when they were doing GO trials in comparison with NOGO trials. In contrast for OP subjects, the emitted spikes were greater during the NOGO trials. The plots indicate that the number of emitted spikes of each neuron was less than 100 in control subjects and greater than 100 in OP subjects during the NOGO trials. These findings support our argument that OP subjects may experience difficulty in inhibiting their inappropriate automated responses when they were expected to not press the button in NOGO trials.

Conversely, by comparing the plots obtained from GO task, we can see that the maximum number of spikes emitted by each neuron was less than 100 spikes in OP subjects. However, this number was increased in MMT and control subjects. Therefore, the spike patterns of the MMT subjects were more similar to the control subjects due to the greater number of emitted spikes, in comparison with OP subjects in GO trials.

H. EEG GO/NOGO Pattern Classification Using the NeuCube Model

In order to learn and classify the EEG signal patterns, the EEG data was entered into a 3-D SNNc for unsupervised learning. Then output classifier neurons were trained using supervised learning algorithm to classify the activity patterns of the SNNc into the predefined classes. The classification accuracy results were evaluated using repeated RRSV. In this experiment, the RRSV method was applied with 50% of the data for training and 50% for testing. In order to optimize classification accuracy, the values of the NeuCube parameters were altered through iterative applications of the NeuCube modules 1–3 as discussed in Section III-B.

In this experiment, the TBR threshold, Connection distance $(D_{\rm thr})$, and STDP rate parameters were changed during 1000 optimization iterations and then the best accuracy was recorded. The parameters that generated the best classification accuracy are reported in Table II. The firing threshold, the mod, and drift parameters were set to 0.05, 0.4, and 0.250, respectively. The classification accuracy results were 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 EEG data.

The methods we used for comparison are: support vector machine (SVM); multiple linear regression (MLR); multilayer perceptron (MLP); and evolving clustering method (see www.theneucom.com). The classification accuracy results of the three experimental sessions for the three output classes of subjects are summarized in Table III.

The classification accuracy results obtained in *session I* show that the control subjects took actions more differently in GO trials versus NOGO trials. Therefore, their EEG spike trains were classified with a higher accuracy of 90.91% in comparison with MMT and opiate subjects. In session II, the classification accuracy of 85% in OP versus CO is higher than the accuracy of 77% in MMT versus CO, which means that the similarity between the EEG data of the MMT and control subjects was greater than the similarity between EEG data of the opiate and control subjects. Consequently, we can conclude that some of the MMT subjects respond to the methadone treatment and their brain activity patterns may be improved and become comparable to the CO subjects. Also, the classification accuracy of 100% in MMT versus OP demonstrates that all MMT subjects were classified correctly into the MMT class. In fact, this result indicates that the EEG data patterns of the MMT subjects are greatly different from opiate subjects.

In session III, the classification accuracy of 90% in OP versus CO is higher than the classification accuracy of 85% in MMT versus CO. These results show that the differences between the brain activity patterns of MMT and control groups can be minimum in contrast to OP group and MMT group. It may represent that the MMT has a potential positive effect on brain function and contribute to functional recovery.

V. CONCLUSION

A NeuCube model includes several methods and algorithms that allow different aspects of EEG data to be studied and analvzed: Spatial mapping of the data 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 related to the data and the brain processes that generated it; supervised learning in an SNN classifier; parameter selection and optimization; and model validation. A NeuCube model is a special type of a LSM [11] that has new features of learning, spatial variable mapping, model visualization, etc. These features make a NeuCube model meaningful in terms of its interpretation for the sake of understanding the spatiotemporal characteristics of the data. The proposed method is a method for modeling brain data in terms of learning functional patterns of dynamic changes across the learned variables (in this case-EEG channels) using SNN. In this study, we used a case study of EEG data captured from three different subject groups (MMT, Opiate, and Control) while undertaking the GO/NOGO cognitive task. The experimental results proved the following phenomena:

- In all experiments, the NeuCube-based models obtained superior classification accuracy when compared with traditional machine learning methods.
- The brain activity patterns of healthy volunteers were significantly different from people with history of opiate dependence. The differences appeared less pronounced in

people undertaking MMT compared to those current opiate users.

- The brain functional pathways of the healthy volunteers were greater and broader than either people undertaking MMT or those opiate users.
- 4) The STBD patterns of people on low dose of methadone appeared more comparable to healthy volunteers compared to those on high dose of methadone.

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