2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

Feasibility of NeuCube SNN architecture for detecting motor execution and motor intention for use in BCI applications

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***Abstract*—The paper is a feasibility analysis of using the recently introduced by one of the authors spiking neural networks architecture NeuCube for modelling and recognition of complex EEG spatio-temporal data related to both physical and intentional (imagined) movements. The preliminary experiments reported in the paper suggest that NeuCube is much more efficient for the task than standard machine learning techniques, resulting in high recognition accuracy, a better adaptability to new data, a better interpretation of the models, leading to a better understanding of the brain data and the processes that generated it.**

I. Introduction

NeuCube is a spiking neural network (SNN) architecture in which both spatial and temporal neuroinformatics data can be encoded as both locations of synapses and neurons, as well as the timing of their spiking activity. NeuCube is capable of learning noisy data either on-line or with low amounts of training. In addition, its brain-like structure can be visualized for greater knowledge extraction than purely statistical or mathematical techniques. NeuCube is based on the idea of physiological Hebbian plasticity, which states that neurons that fire together wire together [1]. Contemporary research indicates that the temporal relationship of firing between the neurons is important in determining the firing association between the neurons. The theory of spike-time dependent plasticity states that pre-synaptic activity that precedes post-synaptic firing can induce long-term potentiation (LTP), reversing this temporal order results in long-term depression (LTD) [2]. The NeuCube is consistent with the theory of spike-timing dependent plasticity as temporal information about spike timing is retained. This advantage may facilitate understanding of recovery from neurological injury and recovery related to rehabilitation. NeuCube was first published in [3] then further developed in [4] and [5]. A block diagram is depicted in Fig.1. The NeuCube architecture consists of the following modules:

- Input information encoding module;
- 3D spiking neural network reservoir (SNNr) module (the Cube);
- Output/classification module;
- Gene regulatory network (GRN) module (Optional).
- Optimisation module (optional)

The input encoding module converts neuroinformatic data into trains of spikes using one of a number of algorithms, including the BSA [6], Population Encoding [7], and Address Event Representation [8] methods. The 3D SNNr is modelled after the human brain, with a population of Leaky-Integrate-and-Fire neurons spatially located according to the Talairach stereotactic atlas. Collected neuroinformatic data is used as inputs to spatially located neurons in the SNNr. The spatial location of these neurons correspond to spatial location of the sections of the brain where the corresponding data was collected (e.g. the location of the EEG electrodes). For example, EEG input channel data are entered into neurons from the SNNr according to the excellent mapping provided in [9]. This preserves the spatio-temporal relationships within the data that is a significant source of information, generally overlooked by other techniques. The number of neurons in the SNNr is scalable. It is set in our experimental NeuCube SNNr at 1471 neurons, each representing 1cm3 of brain tissue [4].

The output module contains a number of classifiers, which are chosen based on the desired output type. These include the deSNN(s,m) classifiers for simple class-based discrimination [10] and the multiSPAN classifier for defined output spike trains [11]. The GRN module was not included in this experiment. In principle, it includes some information on how AMPA, GABAA, GABAB, and NMDA neuronal receptors can modulate the simulated neurons activity much as they do in the real brain.

A focal neurological insult that causes changes to cerebral blood flow, such as in a stroke, can result in mild to severe motor dysfunctions on the contralateral side of the body. Although some spontaneous recovery usually occurs in the first 6 months after stroke only about 14% of people with stroke recover normal use of the upper limb [12]. The driver of

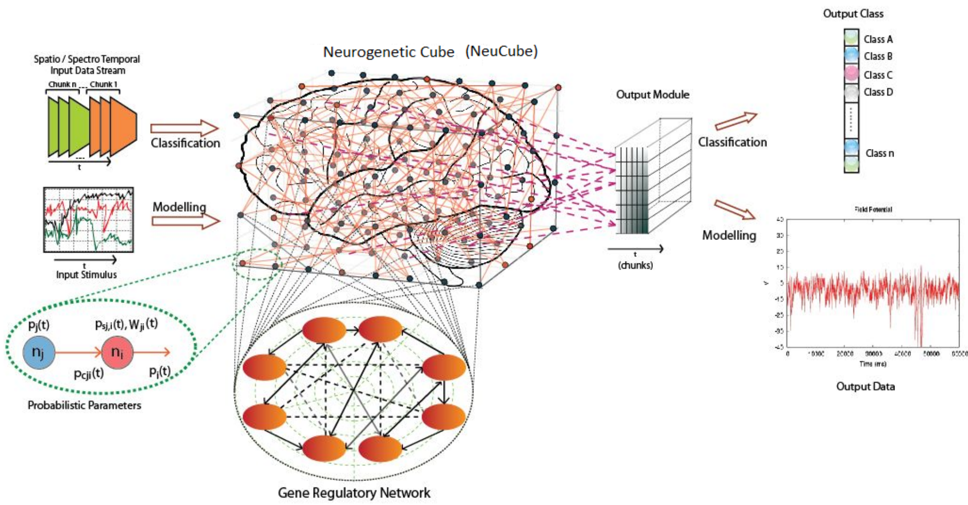

Fig. 1. A block diagram of the NeuCube architecture from [3]

functional recovery after stroke is neural plasticity, the propensity of synapses and neuronal circuits to change in response to experience and demand [13]–[15]. Whilst it is known that frequency and intensity of intervention following stroke is important high intensity rehabilitation is resource-limited. In order to deliver interventions at a high enough intensity and frequency for neural plasticity we need to develop devices that can assist with rehabilitation without the concentrated input of rehabilitation professionals.

Motor imagery (MI), or the mental rehearsal of a movement, is an approach used by rehabilitation professionals to encourage motor practice in the absence of sufficient muscle activity [16]–[18]. MI is thought to activate similar cortical networks as activated in a real movement, including activation of the primary motor cortex, premotor cortex, supplementary motor area and parietal cortices [19], [20]. Recent evidence suggests that although there are common cortical networks in real and imagined movement (frontal and parietal sensorimotor cortices) there are also important differences, with ventral areas being activated in imagined movement, but not in real movement. These specific additional activations in the extreme/external capsule may represent an additional cognitive demand of imagery based tasks.

Recovery of movement control is greater after motor execution training than after MI training alone. Interestingly the combination of MI training with even passive movement generates greater recovery than MI alone [21]. Combining motor imagery with functional electrical muscle stimulation, via Brain Computer Interface (BCI) devices, may result in greater neural plasticity and recovery than motor imagery alone, or motor imagery combined with passive movement. The additional feedback to the brain provided by executing a movement may enhance plasticity and reduce the cognitive demand of motor imagery. Many people following stroke or other neurological disorder have some residual muscle activity but fail to recruit enough motor units at an appropriate speed and pattern, to generate sufficient force to complete the desired movement [22], [23]. A BCI device in which motor imagery triggers an appropriate signal to a functional electrical stimulation system would facilitate the practice of real movements and potentially result in greater neural plasticity and functional recovery.

EEG records brain signals through electrodes on the scalp and is the most widely used method for recording brain data used in BCI devices. EEG is non-invasive and has good temporal and spatial resolution. However, EEG systems have been criticized because of the time consuming and complex training period for the potential user [24]. One advantage of the NeuCube framework is that intensive training of the user is not required as NeuCube classifies naturally elicited cortical activity, rather than a specific component of the EEG signal, such as the P300 wave, the production of which has to be learned by the user. In addition, the NeuCube is capable of learning in an on-line fashion, training as it is used.

We are investigating the feasibility of using NeuCube with EEG data to develop a functional electrical stimulation BCI system that is able to assist in the rehabilitation of complex upper limb movements. Two methods of use are under consideration, firstly for people who have no voluntary activity in a limb who would drive the device using MI, and secondly for people who have some residual activity in their muscles that, in addition to using MI, may augment the device with their own muscle activity. To do this it is important to establish a high degree of accuracy of classification of movement intention and movement execution to ensure that the appropriate electrical stimulation output is then provided. One of the challenges to any BCI system is the extent to which it accurately classifies the input signal.

In [24] real movement, consisting of a pinch grip to a specified force level, compared to a resting state, was used. Data were collected using functional Near Infrared Spectrometry (fNIRS) combined with other physiological data, such as blood pressure and respiratory information. Using hidden Markov Models (HMMs) as the classifier framework accuracies ranging between 79.6% and 98.8% over 2 classes were achieved. Using fNIRS in a trial of MI [24] investigated the classification accuracy of a simple imagined tap of the thumb on a keyboard versus a complex multi-digit tapping sequence. Linear discriminant analysis (LDA) was used in combination with careful selection of the best performing data channel (out of 3 possible channels) and best 4 features for each participant. The study in [25] reported classification accuracies in a 2-class model (simple imagined movement or complex imagined movement) of between 70.8% and 91.7%. A Sparse Common Spatial Pattern (SCSP) optimization technique that reduced EEG channels by disregarding noisy channels and channels thought to be irrelevant was reported in [26], however this approach results in a loss of data that could be informative.

We were interested in determining if it was feasible to use the NeuCube framework as a driver of BCI devices. As a first step we wanted to determine if the NeuCube was at least equivalent in classifying movement tasks as other commonly used methods. As proof-of concept we designed a study that required NeuCube to classify imagined and real movements in two different directions and at rest (wrist flexion, extension or rest). The general hypothesis is that NeuCube using EEG data can correctly identify brain patterns corresponding to specific movements. Previous work from our lab in association with research collaborators has indicated the potential of NeuCube to identify different EEG patterns relating to different imagined movements from a commercially available 14 channel EEG headset. In this trial imagined wrist extension, rest and wrist flexion achieved accuracy in 1 individual of 88%, 83% and 71% respectively [27].

The specific hypothesis for this study was that the NeuCube would accurately classify both single joint real and imagined movements of the hand into one of three classes, flexion, extension or rest. This paradigm built on the earlier work in [27] by increasing the complexity of the task by requiring the NeuCube to distinguish three conditions, two different muscle contraction patterns (flexion or extensor muscle activity) or rest [27]. A secondary hypothesis was that the NeuCube would perform better than other classification methods, including Multiple Linear Regression (MLR), Support Vector Machine (SVM), Multilayer Perceptron (MLP) and Evolving Clustering Method (ECM) [28], along with offering other advantages such as adaptability to new data on-line and interpretability of results.

II. Method

A. Participants

Three healthy volunteers from our laboratory group participated in the study. None had any history of neurological disorders and all were right handed.

B. Protocol

All measures were taken in a quiet room with participants seated in a dining chair. The task consisted of either performing the specified movements or imagining the movements, or remaining at rest. All tasks were completed with eyes closed to reduce visual and blink related artifacts. The movement execution task involved the participant resting, flexing the wrist or extending the wrist. The starting position was from mid-pronation with the forearm resting on the persons lap. The movement intention task involved the participant imagining or performing the movements as described above. Participants were required to imagine or perform each movement in 2 seconds and to repeat that 10 times.

C. Data acquisition

A low-cost commercially available wireless Emotiv Epoc EEG Neuroheadset was used to record EEG data. The Epoc records from 14 channels based on International 10-20 locations (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4). Two additional electrodes (P3, P4) were used as reference. Data were digitized at 128 Hz sampling rate and sent to the computer via Bluetooth. An important factor was that no filtering was applied to the data, either online or offline.

D. Data processing

The data was separated into classes denoting each task. Each set of ten samples was then evenly divided into a training (seen) and a testing (unseen) set. The data was then converted into trains of spikes (one train per channel, 14 in total) with the Address Event Representation algorithm, utilizing a spiking threshold of 6. No other data processing was applied.

E. Classification

Each training sample was presented to the NeuCube once, entered as 14 input streams of EEG continuous data collected at the msec time unit, encoded using AER with a step size of 6. The spiking activity of every neuron was recorded over the time of the sample, and these presented to the deSNNs classifier. The deSNNs was initialized with a Mod of 0.9 and drift factor of 0.25 (empirically established values for this dataset). The synaptic weights for both the NeuCube and the deSNNs were then fixed at their final (learned) values for the validation phase. The unseen data samples were presented in the same way, and the predicted classes recorded. The predicted classes were then compared to the actual classes of those samples.

F. Comparative Study

The NeuCube described above was compared to some popular machine learning methods: MLR, SVM, MLP and ECM. The SVM method uses a Polynomial kernel with a rank 1; the MLP uses 30 hidden nodes with 1000 iterations for training. The ECM (Kasabov and Song, 2002) uses m=3; Rmax=1; Rmin=0.1. Data for these methods is averaged at 8 msec intervals and a single input vector is formed for each session, as is general practice.

III. Results

The classification accuracy of the NeuCube was on average 76%, with individual accuracies ranging from 70-85%. There was a consistent rate of recognition between the real and the imagined movement. In terms of the comparison with other classification approaches, it is clear from the results shown in Table 1 that the NeuCube performed significantly better than the other machine learning techniques with the highest average accuracy over all subjects and samples, whilst the closest competitor was SVM with the second highest average accuracy of 62%. MLR was the poorest performing, with an average accuracy of 50.5%, or just over the chance threshold.

TABLE I. RESULTS OF THE COMPARATIVE STUDY; ACCURACY EXPRESSED AS PERCENTAGE FOR REAL AND IMAGINED MOVEMENTS.

Subject/Session	MLR	SVM	MLP	ECM	NeuCube
1-Real	55	69	62	76	**80**
1-Imagined	63	68	58	58	**80**
2-Real	55	55	45	52	67
2-Imagined	42	63	63	79	85
3-Real	41	65	41	45	73
3-Imagined	53	53	63	53	70
Average (appr.)	52	62	55	61	76

IV. DISCUSSION

This was a feasibility study to investigate the potential of using NeuCube in BCI based rehabilitation devices. In considering the classification accuracies, which ranged from 70-85%, it is important to consider three factors. Firstly, the data were collected in an unshielded room using a commercially available gaming EEG headset, resulting in an EEG signal with relatively high signal to noise ratio. Secondly, there was no processing or feature extraction performed on the data prior to classification, the raw, noisy, EEG data was used as the input. Thirdly, all comparative methods in this study, excepting NeuCube, were validated using Leave-One-Out (all but one sample used for training), while the NeuCube was validated with a more disadvantageous 50/50 (half used for training, half for testing) split. The accuracy of the NeuCube was still significantly higher than the other techniques and would likely rise when trained with leave-one-out paradigms.

Bearing these three factors in mind the classification accuracies obtained using NeuCube are in a similar range to those reported in other research and demonstrates that NeuCube is capable of accurately classifying noisy and relatively low-quality data. In addition, unlike many other approaches NeuCube does not require a lengthy feature extraction process, instead using all the raw data for classification, thus utilizing a rich data set that does not lose any potentially useful data.

We chose to use a relatively cheap and accessible EEG headset because two major factors that prevent the adoption of high technology interventions into rehabilitation practice are cost and complexity. EEG systems commonly used in research and clinical situations are expensive and unlikely to be widely available to rehabilitation specialists. The Emotiv neuroheadset has a limited number of channels with a fixed electrode placement, which may serve to improve usability as it reduces the preparation time and is easy for users to put on themselves.

An advantage of the NeuCube is that it allows for interpretation of results and understanding of the data and the brain processes that generated it. This is illustrated in Fig.2 where the connectivity of a trained SNNr is shown for further analysis. The SNNr and the deSNN classifier have evolvable structures, i.e. a NeuCube model can be trained further on more data and recalled on new data not necessarily of the same size and feature dimensionality. This allows in theory for a NeuCube to be partially trained on highly accurate data captured in a controlled manner with medical devices, and then further trained and adapted to the particular subject with a cheaper, less accurate device such as the Emotiv. This will increase potential uses in clinical and rehabilitation applications.

The large number of parameters that need to be optimized for every experiment to achieve the best results limits the

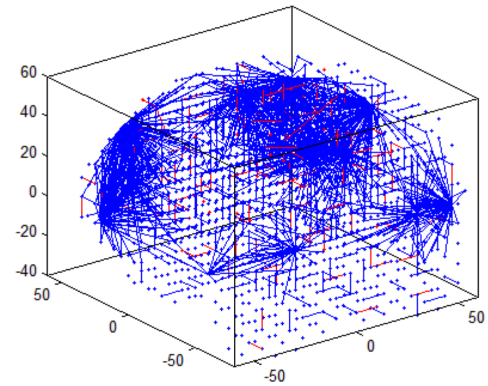

Fig. 2. Example visualisation of the connectome of the trained NeuCube. Blue lines show strong excitatory connections between two neurons, and red strong inhibitory.

current NeuCube. The results presented in this study are obtained through manual parameter optimization. To mitigate this, adaptive and evolutionary techniques (including the GRN discussed prior and quantum-inspired optimization) are being developed for this system, so that parameter selection is automated in a desirable way.

V. CONCLUSION

The results of this study support the premise that NeuCube is feasible to use in BCI based rehabilitation devices. Additionally, the ability of the NeuCube to both spatially and temporally represent brain data and provide visualization of the data could be useful in future applications. Observing changes in neural representation and spike timing throughout rehabilitation interventions could provide valuable information on human learning and adaptation to advance rehabilitation interventions.

ACKNOWLEDGMENT

This work was supported in part by the New Zealand Ministry of Business, Innovation and Enterprise (MBIE) through a Strategic Partnership New Zealand-China grant.

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