Improved Classification and Interpretation of EEG Data using NeuCube for STDP learning and ESN as an on-line Learning Classifier

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***Abstract*—The paper proposes a novel hierarchical recurrent neural network architecture for on-line classification and interpretation of EEG data. It incorporates two dynamic pools of neurons - one based on NeuCube three dimensional structure of spiking neurons connected via spike-timing dependent plastic synapses and another Echo state neural network (ESN) reservoir of sparsely connected hyperbolic tangent neurons that is able to learn on-line to classify the extracted from the Cube spike-rate features. The aim of the work was to interpret and classify in a brain-inspired manner dynamic spatio-temporal brain EEG data. The achieved results demonstrate improved classification accuracy on a benchmark data set along with a good interpretability of the data. In future, the proposed method can be used for classification of other brain spatio-temporal data, such as ECOG and fMRI.**

***Index Terms*—SNN, ESN, NeuCube, EEG, classification, on-line learning, spiking neurons**

I. Introduction

Electroencephalography (EEG) is a method to record the electrical activity of the brain. It is typically non-invasive, with the EEG electrodes placed along the scalp. The measured in this way signals represent the postsynaptic potentials of pyramidal neurons in the cortex. Since the electrical activity in the brain surface originates in the deeper brain ares that do not contribute directly to an EEG recording, their influence could be assessed accounting for the electrodes orientation and distance to the source of the activity.

By far EEG has been applied to numerous domains from brain–computer interface [], emotion [], cognition [], brain diseases [] etc. Through the years the EEG data processing methodology has evolved from simple methods, such as mean and amplitude comparison to complicated methods, such as connectivity topology and deep learning [12]. In particular, deep learning exhibits better performance in EEG classification in comparison with the conventional methods.

In order to exploit EEG data for analyses the first step traditionally is to ”decode” them [25], [26] or to extract a range of signal properties referred to as ”features” which are then utilized for detection or classification purposes [19]. The analyses outcome is largely influenced by the quality of extracted features. A recent trend in EEG features extraction and processing exploits recurrent neural networks [24] and especially a member of reservoir family - fast on-line trainable Echo state networks (ESN) [17], [18], [20]–[23].

Nevertheless, accurate on-line classification and explanation of dynamic spatio-temporal brain data, such as EEG is still an open problem. While there are many methods introduced for brain data classification, most of them lack explainability in relation to the measured brain functions as spatio-temporal patterns. Accounting for spatial brain structure in the design of RNN decoders or feature extractor became a natural direction of work nowadays [11]. Recently developed brain-inspired spiking neural network (SNN) models, such as NeuCube [4], [13]–[16], demonstrated a good classification accuracy and excellent explanation of the spatio-temporal patterns learned from spatio-temporal brain data, such as EEG and fMRI [5].

This paper explores the integration of the Cube module with an ESN classifier, aiming at improved classification accuracy in an on-line learning mode. The proposed method makes use of two types of information contained in the data, spike-timing, learned in an unsupervised mode in the Cube, and spike-rate or spiking frequency features, captured and classified in the ESN in an on-line mode.

Further the paper is organized as follows: section II presents briefly NeuCube and ESN structures and the proposed hierarchical architecture NeuCube-ESN for EEG on-line classification; section III presents the classification results on a benchmark example of EEG data for wrist movement and compares the achieved accuracy with NeuCube classification results from []; finally the concluding remarks summarize the main achievements in the presented work and points the directions for future work.

II. NeuCube - ESN Brain Data Architecture

A. NeuCube Structure

The NeuCube architecture is an open one, allowing for new algorithms to be explored for encoding, learning, classification, regression. It consists of three parts [5]:

- Data encoding part, where input streaming data is encoded into spike sequences using a suitable algorithm [8].
- A 3D Cube structure of spiking neurons, where every neuron has a 3D spatial coordinates defined through the use of brain-template, such as Talairach or MNI. Initial connections were generated randomly based on the distances between each two neurons.
- SNN classifiers of evolving spiking neuron networks (eSNN) or dynamic evolving spiking neuron networks (deSNN) [6] are used to separate the outputs of NeuCube into classes.

After encoding of the spatio-temporal EEG data into sequences of spikes (spike-time information), the Cube, structured according to a brain template, receives as input EEG recordings at neurons corresponding to the electrodes' positions on the scull. As a result all neurons in the Cube generate spike trains whose dynamics depends on the input signal as well as on both the connectivity within the Cube (small world connectivity at the beginning) and on the spike time dependent plasticity of the connections (synapses). Finally the output classifier takes the Cube spike trains as classification features.

B. ESN Structure

Echo state networks (ESN) belong to a novel and rapidly developing family of reservoir computing approaches [1]–[3] whose aim was development of fast trainable recurrent neural network (RNN) architectures able to approximate nonlinear time series dependencies. The detailed structure of an ESN reservoir is shown on Fig 1.

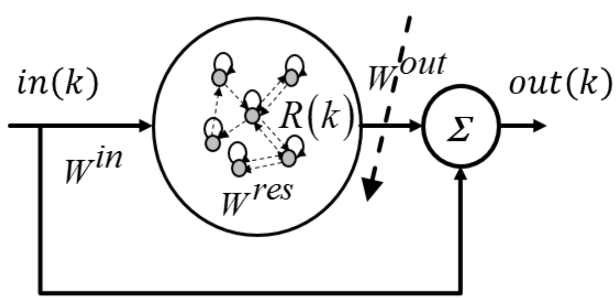

Fig. 1. ESN reservoir structure.

It incorporates a pool of neurons with sigmoid activation function f^{res} (usually the hyperbolic tangent) that has randomly generated recurrent connection weights. The reservoir state $R(k)$ for the current time instant k depends both on its previous state $R(k-1)$ and the current input $in(k)$ as follows:

$$R(k) = (1-a)R(k)+af^{res}(W^{in}in(k)+W^{res}R(k-1)) \quad (1)$$

Here W^{in} is the matrix of input to reservoir connection weights that are randomly generated; W^{res} is the internal reservoir connection weight matrix that is sparse and also randomly generated according to recipes given by [2], [3], namely its spectral radius has be below 1; $a \in [0, 1]$ is leaking rate parameter. The ESN output $out(k)$ is calculated as a function f^{out} (usually identity function) of the linear combination of the current reservoir states $R(k)$ or of concatenation of the input and reservoir states $[R(k)\ in(k)]$ weighted by the output weight matrix W^{out}:

$$out(k) = f^{out}(W^{out}[R(k)\ in(k)]) \quad (2)$$

The ESN hyper parameters that are subject of manual tuning, usually via grid search, are the reservoir size (number of neurons), reservoir connection matrix sparsity and spectral radius and leaking rate. Additionally input and output scaling could be included.

The only trainable parameters of ESN are the output weights W^{out}. In case of identity output function the least squares method is applied to train the ESN in a single iteration. For the aims of on-line training the recursive version of least squares (RLS) can be applied too [1].

C. NeuCube-ESN Brain Data Classifier

The proposed novel brain data classifier called NeuCube-ESN is a hierarchical RNN composed by two recurrent architectures - a brain inspired NeuCube, that is a spatio-temporal structure of SNN neurons and a fast trainable ESN as a nonlinear time series classifier. The overall structure is shown on Fig. 2.

The following algorithm depicts the functionality of the proposed classifier:

- A 3D SNN Cube is initialised by defining the size of the Cube of N neurons and their 3D locations, including positions of EEG electordes.
- In contrast to NeuCube approach, here the EEG data is scaled and fed into the Cube as generating currents into neurons corresponding to electrodes positions.
- During the input of each EEG sample unsupervised STDP learning rule is applied on the Cube and spiking activity of all neurons was recorded. For a given time window D (e.g. 100 ms) the spiking frequency of each of the N neurons in the Cube is calculated. Thus for duration of a sample EEG record of T ms a new time series of Cube firing rates is extracted as feature vector of size $T/D \times N$.
- The output classifier is an ESN reservoir with M neurons. It receives generated by Cube time series feature per

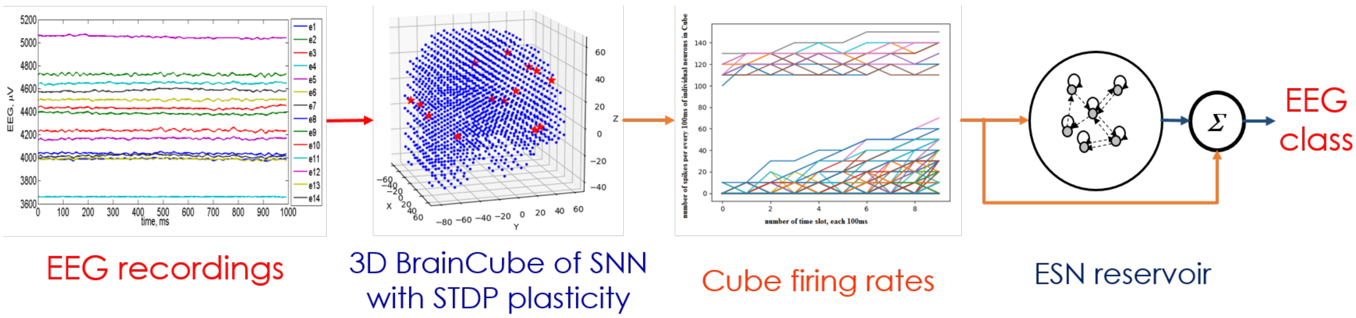

Fig. 2. Proposed NeuCube - ESN structure.

given EEG sample. The achieved reservoir state after presentation of each EEG sample feature vector was send to its readout and the output weights were adjusted to predict the correct EEG class. The training was done via RLS in on-line mode.

The hyper-parameters parameters of the Cube and the ESN, e.g. refractory period and membrane threshold potential of spiking neurons, STDP learning rate, size, sparsity and leakage rate of ESN reservoir, have to be optimised for a best classification accuracy.

The connectivity obtained in the Cube SNN after presentation of each EEG sample can be analysed as spatio-temporal patterns to better understand each class of the brain activity captured as EEG data.

III. Results

The benchmark data used here to illustrate the proposed method is taken from [10]. The EEG data of 14 channels $Emotiv$ measuring device were collected for $T = 1000$ ms with sampling frequency of 128Hz. The test subject is asked to perform three different types of wrist movement - up, down and straight - that are separated into three EEG classes and 20 examples per class are collected, making all number of samples 60.

The 3D structure of the used Cube from the NeuCube architecture [4], [5] is shown on Fig. 2. The blue dots are neurons positions while the red dots mark the EEG electrodes positions as input neurons. The Cube is designed according to the scalable Talairach atlas, in this cases using $N = 1471$ neurons [7]. The location of the input neurons, corresponding to the used in this case 14 EEG channels, is defined following the 10-20 EEG location system.

The Cube initial randomly generated connectivity is shown on Fig. 3. The red lines correspond to excitatory connections while the blue ones - to the inhibitory connections. Small-world connectivity method is used to derive the initial connections in the Cube, where the closer two neurons are in the 3D space, the higher the probability of them to be connected. Initial connections are assigned small weights, with 80% positive and 20% negative values.

The Cube is simulated in NEST Simulator, version 3.3 [27], using leaky integrate-and-fire neuron model with the default parameters: $t_{ref} = 2$ ms, $V_{th} = -55$ mV and STDP synapses with learning rate $\lambda = 0.01$.

The ESN was implemented in Python.

Fig. 4 shows connectivity changed after presentation of one EEG recording example. It is observed that the connections strength as well as the number of excitatory connections increased.

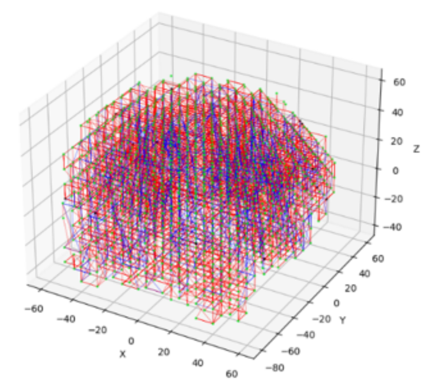

Fig. 3. Brain template initial connections.

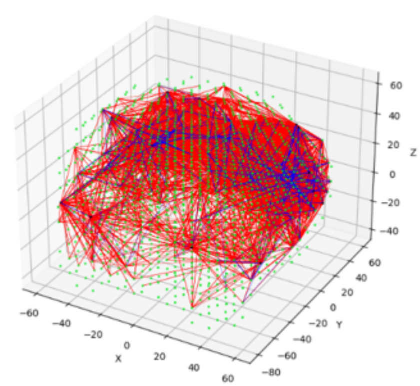

Fig. 4. Brain template of connections after presenting only one example of EEG data

For the defined size of time window $D = 100$ ms the extracted time series features per EEG sample are of 1471×10 dimension.

In order to tune ESN classifier hyper-parameters the exhaustive grid search was performed. The best results were achieved with: reservoir size $M = 4500$, leaking rate $a = 0.8$ and reservoir connectivity weight matrix sparsity 0.6.

Since the ESN output is continuous value in range $[-1, 1]$, for the aim of classification the target values corresponding to three classes were -1, 0 and $+1$ respectively.

Fifty percents of data were used for training and the rest for testing of the classifier accuracy. K-fold cross validation was performed with $k = 6$.

Figure 5 shows test data vs classification result. The achieved mean test MSE from all 6 folds was about 0.00329 which demonstrates a perfect classification. Having in mind that the ESN output values close enough to the target one will result in correct classification, e.g. -0.995 will be rounded to -1, we can say that our classifier achieved 100% accuracy.

Fig. 5. Test data vs ESN predictions.

The reported in [10] accuracy on test data for the same benchmark EEG data set using standard NeuCube with deSNN classifier is 86.67%.

IV. Conclusion

The classification accuracy, demonstrated on the case study benchmark EEG data and shown in Fig. 5 is close to 100%. This is significantly better then the accuracy achieved in NeuCube when using deSNN as a classifier (86.67%). The reason is the integration of both spike-time and spike-rate information extracted from the data, that better represents the complexity of the EEG data. The Cube learns the spike-timing information, while the ESN - the rate/frequency information from data, captured in the neurons of the Cube. In a the previous use of NeuCube on the benchmark data, the deSNN classifier was used [6] that uses spike-time information for classification, which type of information was used also in the Cube.

Future work is planned of optimising the parameters of both the Cube and the ESN so that the model can be implemented on a neuromorphic hardware chip. The team also plans to apply this method on other spatio-temporal brain data, such as ECOG and fMRI.

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