2014 5th IEEE RAS & EMBS International Conference on
Biomedical Robotics and Biomechatronics (BioRob)
August 12-15, 2014. São Paulo, Brazil

EEG-Based Classification of Upper-Limb ADL Using SNN for Active Robotic Rehabilitation*

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Abstract— **Repetitive activities of daily living (ADL) and robotic active training are commonly practised in the rehabilitation of paralyzed patients, both of which have been proven rather effective to recover the locomotor function of impaired limbs. ADL classification based on electroencephalogram (EEG) is of great significance to perform active robotic rehabilitation for patients with complete spinal cord injury (SCI) who lose locomotion of affected limbs absolutely, where surface electromyography (sEMG) or active force signal can hardly be detected. It is a challenge to achieve a satisfying result in neuro-rehabilitation robotics using EEG signals due to the high randomness of the EEG data. A classification method is proposed based on spiking neural networks (SNN) to identify the upper-limb ADL of three classes with 14-channel EEG data. The continuous real-number signals are firstly encoded into spike trains through Ben's Spike Algorithm (BSA). The generated spikes are then submitted into a 3-D brain-mapped SNN reservoir called NeuCube trained by Spike Timing Dependant Plasticity (STDP). Spike trains from all neurons of the trained reservoir are finally classified using one version of dynamic evolving spiking neuron networks (deSNN) - deSNNs. Classifications are presented with and without NeuCube respectively on the same EEG data set. Results indicate that using the reservoir improves identification accuracy which turns out pretty promising despite that EEG data is highly noisy, low frequently sampled, and only from 14 channels. The classification technique reveals a great potential for the further implementation of active robotic rehabilitation to the sufferers of complete SCI.**

Index Terms— **Active robotic rehabilitation, ADL classification, EEG, SNN, NeuCube.**

I. INTRODUCTION

The number of patients with paralysis is currently growing significantly with an accelerating increase rate resulting from high incidence of cerebrovascular diseases and various accidents. Rehabilitation is a primary therapy to them after instant treatment, which is usually a long-time process, and sometimes may continue throughout most of their entire lifetimes. In the traditional therapy the neurorehabilitation process of affected limbs of paralyzed sufferers is normally carried by physiotherapists to practise patients movement passively. Deficient training modes as well as non-repetitive exercises result in limited rehabilitation effect, while the traditional method is costly, time-consuming and labour-intensive. Rehabilitation robots can provide various repetitive training strategies, reduce the cost and time consumed and also release patients and therapists from heavy physical burden, resulting in better rehabilitation methods.

Rehabilitation exercises with robotic devices can be broadly classified into two categories, passive and active training strategies, depending on whether voluntary contribution of patients is involved. Passive training is actuated completely by robots which carry the affected limbs to perform predefined movements requiring no autonomous participation of patients. Active training on the other hand always adapts to the voluntary effort of patients while robots provide necessary assistance to implement desired movements, which tends to be more effective for limb rehabilitation [1], [2] than passive exercises since the paralyzed patients are motivated to contribute the training practices initiatively. The surface electromyography (sEMG) and active force signals are usually gathered to extract voluntary movement intention of patients [3]–[9], which requires that the injured limbs can still partially control the muscle contraction and produce some strength at least. Therefore, active robotic rehabilitation usually applies to incomplete paralyzed patients who retain or regain certain locomotor function of impaired limbs.

Repetitive activities of daily living (ADL) such as reaching to grasp for upper limbs and walking for lower limbs are validated as fairly helpful to restore the locomotor function of patients with paralysis [10]–[13]. Due to the real-life meaning, task-oriented property and multi-joint coordination, ADL keep enhancing positive feedback to central nervous system of paralyzed sufferers more intensively than simple meaningless movements such as single-joint extension/flexion or abduction/adduction. Hence, ADL are usually adopted as training movements to exercise injured limbs in traditional therapy as well as robotic rehabilitation. Typically, body weight support treadmill training (BWSTT) is a commonly practised movement for the paraplegic patients to recover the walking abilities of affected lower limbs, widely applied in both traditional and robotic rehabilitation.

The exercises combining active robotic training with ADL are supposed to be very effective for rehabilitation. But for the sufferers with complete spinal cord injury (SCI) whose locomotor function is totally lost, the voluntary movement intention is almost impossible to be obtained from sEMG or active force of injured limbs. These signals generated by patients are too weak to be detected since they can barely

*This research is supported in part by the National Natural Science Foundation of China (Grants 61225017, 61175076, 61203342), and the International S&T Cooperation Project of China (Grant 2011DFG13390)

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control the ill limbs, while electroencephalogram (EEG) is still strong enough to be collected for the extraction of voluntary movement intention. Hence, EEG-based classification of ADL is of great significance and has a great potential to implement active robotic rehabilitation for patients with complete SCI. It is however quite challenged to achieve a satisfying identification result due to the high randomness of EEG data. In this paper, classification of upper-limb ADL is performed only with the use of EEG data based on spiking neural networks (SNN). The proposed method presents a promising accuracy of identification in spite of the simple equipment and consequently the noisy and low frequently sampled EEG data only from 14 channels.

The remainder of the paper is organized as follows. Section II introduces the equipment, three ADL scenarios and the protocols for EEG data acquisition. In Section III, the procedures of EEG data classification are described in detail. EEG data encoding, the 3-D brain-mapped SNN reservoir called NeuCube as well as the classifier are presented in corresponding subsections. Section IV depicts the classification results and raises some discussion, where the identification accuracy is compared between the classification techniques with and without NeuCube. The last section comes up with the conclusion and future work.

II. EEG Data Acquisition

The non-professional equipment, *Emotiv*, was employed for EEG data acquisition in this study. It has only 14 channels with low sampling frequency of 128Hz, i.e. merely 128 data points can be recorded per second for each channel. *Emotiv* is inexpensive and very easy-to-use, but the number of channels is highly limited and the EEG signals can be easily interfered by even slight body and facial movements such rolling eyeballs. Hence, EEG data collected with the equipment was expected to be rather noisy. It is quite a challenge to obtain satisfying classification results from EEG data set with high noise, insufficient channels and low sampling frequency.

We are aiming at the development of personalised neuro-rehabilitation robots that can be adapted to a person based on his/her EEG data. To illustrate this method, one healthy male subject was involved in the EEG data acquisition. He was asked to perform three different types of ADL with the left upper limb. The movement scenarios are shown in Fig. 1, including idle state, eating and pulling trousers. For idle state, the subject was told to just relax and stay still as indicated in Fig. 1(a), trying not to think about anything. For the other two activities, the subject was told to begin with idle state and finish with the gestures shown in Fig. 1(b) and 1(c) respectively. During all three ADL, he maintained standing orientation with his eyes closed, meanwhile tried to reduce unnecessary movements for the purpose of decreasing potential interference to EEG signals as much as possible.

One supervisor was required to coordinate the whole process of data acquisition. However, it is not necessary that he/she has accepted medical training. The subject started each activity with the voice command of 'GO' from the supervisor, and finished the movement within 1 second. The collection of EEG data was initiated by the supervisor at the same time with the duration of 1 second as one sample, i.e. each sample contained 128 data points for each channel. Before the data acquisition, the subject was allowed to practise the ADL as much as needed till he felt ready. After that, the subject was asked to repeat each movement for 10 times, i.e. 10 samples for each ADL were collected overall, which were divided into two subsets: 5 of the samples were used to train the NeuCube and the classifier, and the remaining 5 ones for validation.

(a) Idle State (b) Eating (c) Pulling Trousers

Fig. 1. EEG Data Collection Scenarios

III. EEG-Based Classification of ADL

Fig. 2 shows the principle block of active robotic rehabilitation based on the classification of ADL, where the SNN-based reservoir and classifier are employed to visualize, process and identify the input signals of EEG data collected from subjects. The real-number raw EEG data of continuous value has to be firstly converted into spike trains with the encoding method. Then the generated spike trains are sequently fed into a 3-D brain-mapped reservoir called NeuCube which is actually composed of large scale SNN. Afterwards, the SNN-based classifier presents identification of ADL with spike trains produced by all the neurons of trained NeuCube. The identification results can be further considered as the control command of robotic rehabilitation devices to perform active training exercises on paralyzed patients with complete SCI when he/she is imagining the movements, so that robots can assist the impaired limbs to practise the ADL which patients desire. This will be the concentration and elaborately investigated in our future work.

The encoding method needs to be tuned to ensure an appropriate density of spike trains and that EEG data can be well recovered from the converted spike trains. The SNN-based reservoir and classifier have to be trained in sequence before the classification method can be recalled. The training is performed twice separately using different learning methods with the following procedure. Firstly, NeuCube learns the spike trains converted from the training samples of EEG data through an unsupervised learning method. Afterwards, the SNN classifier learns spike trains from the trained NeuCube on training samples with a supervised learning method. Before real-time application, the trained system is supposed to be performed on the test samples to validate its feasibility and classification accuracy.

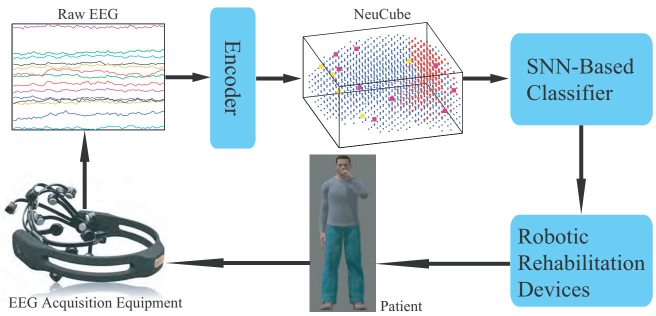


Fig. 2. Principle Block of Active Robotic Rehabilitation with EEG

A. Encoding

Real-number signals of continuous value are converted into spike trains commonly utilizing three encoding methods, which are Population Rank Coding (PRC), Address Event Representation (AER) and Ben's Spike Algorithm (BSA) [14]–[16]. BSA is employed to encode the EEG data collected from the ADL scenarios described above since the analog EEG signals recovered from spike trains are much more consistent with the original ones when using BSA than the other two encoding methods.

EEG data was firstly normalized into the range of $[0 \quad 1]$ where 0 represents the minimum and 1 the maximum value, and then the normalized signals are transformed into spike trains with BSA encoding method where a linear finite impulse response (FIR) filter and a threshold is required. The size of FIR filter as well as the threshold need to be well tuned to achieve the best recovery of EEG from the encoded spike trains by minimizing the error err represented as

$$err = \frac{\sum |eeg - eeg_{est}|}{\sum eeg} \tag{1}$$

where: eeg represents the original recorded EEG data; eeg_{est} is the reconstructed data from BSA encoded spike trains. For the particular EEG data set sampled from aforementioned ADL scenarios, the size of FIR filter was optimized as 7 and the threshold as 0.679 by trial and error. The corresponding err in (1) is minimized to 0.16%. The FIR filter employed in BSA to encode EEG data is indicated in Fig. 3, coefficients of which are normalized so that the summation of them equals to 1.

With the filter size and threshold optimized above, the encoding and decoding results are shown in Fig. 4 with the time length of 1 second. The estimated and the original EEG signal of one channel from one sample are compared in Fig. 4(a) where the red dashed line indicates the EEG data decoded from spike trains, and the actual EEG data is represented by the solid line in blue. The comparison reveals EEG data is well recovered from the spike strains. Fig. 4(b) shows the corresponding spike trains encoded by BSA method. Each vertical bar represents a spike emitted at this channel at that moment. An appropriate density of spike trains is also ensured by BSA encoding.

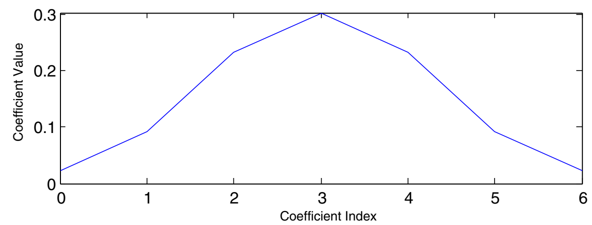
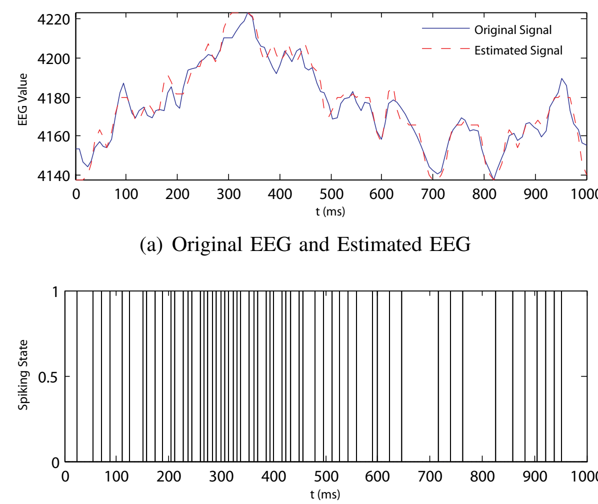


Fig. 3. Curve of Linear FIR Filter



(a) Original EEG and Estimated EEG

(b) EEG Spiking

Fig. 4. BSA Encoding Method

B. NeuCube

NeuCube is a 3-D SNN reservoir that specifically deals with brain data such as EEG and functional magnetic resonance imaging (fMRI) data proposed by N. Kasabov [17], [18]. It is an approximate map of human brain with its neurons assigned to particular locations based on brain coordinate systems such as Talairach coordinate system and Montreal Neurological Institute (MNI) atlases. Each neuron in NeuCube belongs to a specific functional and structural area as in a human brain according to its (x,y,z) coordinates. NeuCube can provide high-level visualization of brain activity during the data processing. We can visualize how the spike signals transmit in the brain, which brain areas are highly or barely activated, whether connections between neurons are strengthened or weakened, and how the connections as well as neuron spiking activities change from random initialization to a stable pattern during training on a particular data set.

Two neuronal models are commonly used in NeuCube, leaky integrate and fire model (LIFM) and probabilistic model. Although studies show that better results can be derived from probabilistic model, it is difficult to be well tuned since there is too many parameters and this task is planned as future work. Therefore, LIFM is used in this study, and the total post synaptic potential (PSP) of neuron i at time t, $u_i(t)$ is calculated as

$$u_i(t)=\begin{cases}0, & t<t_s(i)+t_r\\ u_i(t-t_u)+\sum\limits_{j=1,\cdots,1471}e_j(t)w_{ji}(t)-u_{leak}, & \text{otherwise}\end{cases} \quad (2)$$

where: $t_s(i)$ is the last spiking time of neuron i; t_r denotes the refractory time of the neurons after a spike emitted; t_u represents one time unit; $e_j(t) = 1$ if there is a spike at synapse j at time t, $e_j(t) = 0$ otherwise; $w_{ji}(t)$ is the connection weight from neuron j to i, i.e. at synapse (j, i) at time t; u_{leak} is leaky potential per time unit. When the PSP of a neuron is over the potential threshold, a spike will be emitted and the PSP will be reset to an initial value which is 0 in this case. The neuron will not response to any input during a refractory time.

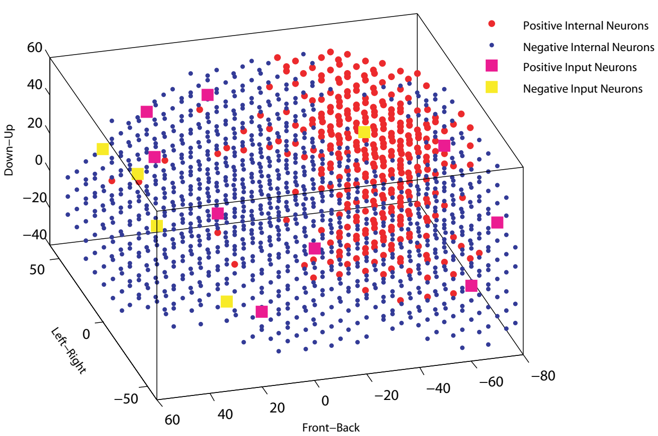


Fig. 5. Structure and Visualization of NeuCube

The structure and visualization of NeuCube developed in this study are illustrated in Fig. 5, where there are 1471 neurons in total with locations based on Talairach coordinate system, each spiking neuron representing approximately 1cubic centimeter from the Talairach atlas. Fourteen of them are input neurons whose coordinates correspond to the positions of the 14-channel electrodes of Emotiv equipment located on the scalp, represented in Fig. 5 by the square markers. Two statuses of input neurons, spiking and non-spiking, are determined directly by the input spike trains encoded from EEG data, represented in magenta and yellow respectively. The remaining 1457 neurons are internal ones, indicated by the dots which also have only 2 activities, spiking and non-spiking as well, represented in red and blue respectively. For the internal neurons, it is determined by the neuronal model whether they are spiking or not.

The connection weights between the neurons of NeuCube are randomly initialized based on small world connection (SWC) [19] principle determined by

$$w_{ij}(0) = c_{ij}s_{ij}\alpha_{ij}\mathrm{e}^{-d_{ij}},\ \forall i,j = 1,\cdots,1471 \quad (3)$$

where: $c_{ij} = 1$ if there is a connection from neuron i to j, $c_{ij} = 0$ otherwise; $s_{ij} = 1$ if the connection is excitatory, $s_{ij} = -1$ inhibitory; α_{ij} is a random factor that follows unform distribution within the range of $[0 \quad 1]$; d_{ij} is the Euclidean distance between the two neurons i and j. The initial connections between the neurons of NeuCube satisfy with the constraints as follows.

- Connections are established randomly following the uniform distribution.
- No connection exists between neurons when the distance is greater than a threshold d_{th}, which in this case is selected as one sixth of the maximum distance between two neurons in NeuCube, $c_{ij} = 0,\ \text{if}\ d_{ij} > d_{th},\ \forall i,j = 1,\cdots,1471.$
- No neurons are connected to input neurons, $c_{ij} = 0,\ \forall i = 1,\cdots,1471,\ j = 1,\cdots,14.$
- No neurons are self-connected, $c_{ii} = 0,\ \forall i = 1,\cdots,1471.$
- All neurons are one-way connected, $c_{ij}c_{ji} = 0,\ \forall i = 2,\cdots,1471,\ j = 1,\cdots,i-1.$
- Connections from input neurons to internal ones are excitatory with positive weights, $s_{ij} = 1,\ \forall i = 1,\cdots,1471,\ j = 1,\cdots,14.$
- Eighty percent of internal connections are excitatory with positive weights, and 20% of them are inhibitory with negative weights.

It is indicated in (3) that the connection weights decrease with the distances between neurons increasing, which agrees with the basic concept of the SWC.

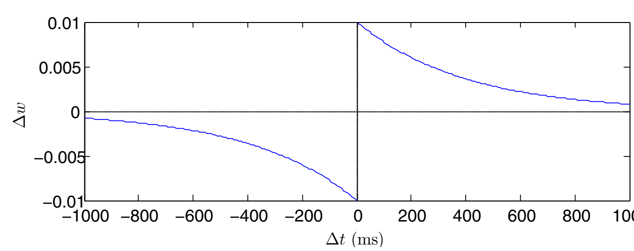


Fig. 6. Curve of STDP Learning Rule

Spike Timing Dependant Plasticity (STDP), utilizing a Hebbian form of plasticity in terms of long-term potentiation (LTP) and long-term depression (LTD) [20], is used as the learning method to train NeuCube. The connection weights between neurons are adjusted as

$$\Delta w = \mathrm{sgn}(\Delta t)A\mathrm{e}^{-|\Delta t|/\tau} \quad (4)$$

where: Δw is a adjustment to connection weight; $\Delta t = t_{post} - t_{pre}$ is the time difference of two consecutive spikes generated by post-synaptic and pre-synaptic neurons; A is a scaling factor; τ is a time constant.

The learning curve of STDP illustrated in Fig. 6 indicates that connection weights are strengthened or weakened based on the spiking timings of post-synaptic and pre-synaptic neurons. Connected neurons can learn consecutive temporal associations from data through STDP to adjust the connection weights. If pre-synaptic neuron spikes first, i.e. the difference of the spike time between the post-synaptic and pre-synaptic neurons is positive, the connection weight between the two neurons increases, i.e. LTP occurs, otherwise it decreases, i.e. LTD proceeds.

C. Classifier

Classifiers of evolving spiking neuron networks (eSNN), dynamic evolving spiking neuron networks (deSNN) [21] and Spike Pattern Association Neuron (SPAN) [22] are usually used to deal with the outputs of NeuCube which are spike trains of its all neurons. For this study, one version of deSNN - deSNNs is employed which is proved a more suitable classifier than the others through experiments.

During the training phase, one new output neuron i is created for each input training sample in deSNNs, and the connection weights are initialized based rank order rule as

$$\omega_{ji}(t_0) = \alpha mod^{order_{ji}} \tag{5}$$

where: $\omega_{ji}(t)$ represents the connection weight from input channel j to neuron i at time t; t_0 is the time when the first spike at input channel j occurs; α is a learning parameter; mod is a modulation factor that defines how important the order of the first spike is; $order_{ji}$ is the rank order of first spike at input channel j among all the spikes having arrived at neuron i. For the first spike to neuron i, $order_{ji} = 0$ and increases according to the input spike order at other input channels.

After initialization, the connection weights become dynamic and are adjusted through the Spike Driven Synaptic Plasticity (SDSP) algorithm as

$$\omega_{ji}(t) = \omega_{ji}(t - t_u) + f_j(t)\mathrm{D},\ \forall t = t_0 + t_u, \cdots, T \tag{6}$$

where: $f_j(t) = 1$ if there is a subsequent (non-first) spike at input channel j at time t, and $f_j(t) = -1$ otherwise; D is the drift parameter; T is the time length of each sample. After the weight vector is finalized, the optional procedure is to combine the new created neuron into a existing one of the same class if the distance between the two weight vectors is less than a threshold. The distance comparison usually involves the initial value $\boldsymbol{\omega}(t_0)$ and the final $\boldsymbol{\omega}(T)$. The weight vector of the combination is the average of the original two. It is however not performed in this case.

During the testing phase, a new output neuron is generated for each testing sample, in the same way as the output neurons are created during the training phase. The connection weight vector of the newly created neuron is then compared with the already existing neurons created during training phase using Euclidean distance. The testing sample belongs to the class which the closest output neuron represents. After the sample classified, the new neuron will be removed. As the synaptic connection weights are dynamic, the distance should be calculated possibly using both the initial $\boldsymbol{\omega}(t_0)$ and the final $\boldsymbol{\omega}(T)$ connection weigh vectors. But in this case, only the final weight vector $\boldsymbol{\omega}(T)$ is used.

IV. Classification Results and Discussion

Two separate classifications are performed using the classifier of deSNNs with and without NeuCube on the samples of EEG data collected from the aforementioned scenarios of ADL. Results of the two methods are compared to illustrate how the 3-D reservoir affects the identification accuracy. Table I presents the results of the two classifications on different data sets which are overall, training and test samples, as well as test samples of classes 1, 2, and 3 which represent idle state, eating and pulling trousers respectively. The accuracy is up to 86.67% on test samples when NeuCube is employed, which is quite a promising result despite the low-grade EEG equipment utilized in this case only with 14 channels and sampling frequency of 128Hz.

TABLE I
Classification Accuracy on Different Data Sets

	Overall	Training	Test	Class 1	Class 2	Class 3
With NeuCube	93.33%	100%	86.67%	80%	100%	80%
Without NeuCube	86.67%	100%	73.33%	80%	100%	40%

Table II is the confusion matrix on the test samples using deSNNs with and without NeuCube. Only 2 samples are misclassified when NeuCube is employed, 1 sample of class 1 misclassified to class 3 and 1 sample of class 3 misclassified to class 2. While there are 4 misclassified samples when classification is accomplished without the reservoir, 1 sample of class 1 misclassified to class 3 and 3 samples of class 3 misclassified to class 2. The major improvement focuses on the identification of samples belonging to the third class which is illustrated at the last row of the confusion table.

TABLE II
Confusion Matrix on Test Samples

		Predicted Class					
		With NeuCube			Without NeuCube		
		Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Actual Class	Class 1	4	0	1	4	0	1
	Class 2	0	5	0	0	5	0
	Class 3	0	1	4	0	3	2

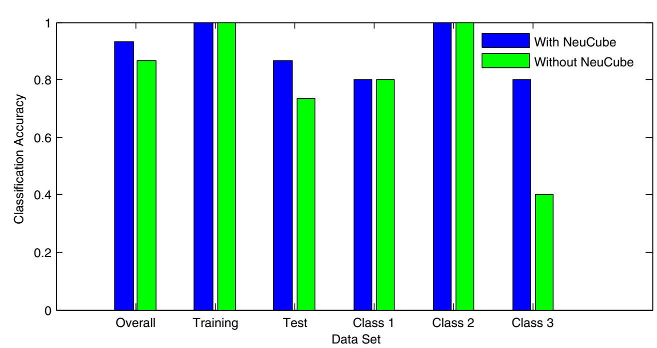


Fig. 7. Classification Accuracy on Different Data Sets

The classification accuracy of deSNNs with and without NeuCube on different data sets is also presented and compared in Fig. 7, where the blue and green bars indicate the results of the classifier with and without the 3-D reservoir respectively. It is obviously that NeuCube improves the classification accuracy. The reservoir maps the 14-channel spike trains into large scale SNN, which not only provides a high-level visualization of EEG data mimicking the brain activities but also generates more distinguishable features. The technique has a great potential for rehabilitation evaluation by visualizing EEG data in different stages of a gradual therapy. And the highly distinguishable outputs reveal a great potential for the further implementation of active robotic rehabilitation to the sufferers of complete SCI.

V. Conclusion and Future Work

An EEG-based classification of upper-limb ADL has been accomplished using SNN. Promising classification results are achieved even though the EEG acquisition equipment is low-grade and consequently the EEG samples are of high noise, low frequent collection as well as limited number of channels. This output can be further employed as the control command for the purpose of active robotic rehabilitation to paralyzed sufferers with complete SCI. Comparison between classification results of deSNNs with and without NeuCube has verified that the 3-D brain-mapped reservoir can improve the classification results as it performs deep learning of spatio-temporal EEG patterns. The SNN-based NeuCube has been proven an effective method to process, visualize and classify EEG data.

For the future work, similar studies will be performed with more advanced EEG equipment which can collect EEG data of less noise and sufficient channels (128 to be specific) with much higher sampling rate. Better results can be expected given the satisfying outcome of the current research. Since paralyzed patients with complete SCI cannot actually move their affected limbs, EEG data collected from imaginary scenarios will be explored for the classification instead of data from actual movement. All the ADL classified in this paper are short discrete movements and carried out by upper limbs. Further work will investigate the classification of lower-limb ADL as well as continuous movements. Most importantly, the classification techniques and robot control schemes will be combined together to implement active robotic training strategies which can even apply to the rehabilitation of paralyzed patients with complete SCI.

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