EEG Comparison Between Normal and Developmental Disorder in Perception and Imitation of Facial Expressions with the NeuCube

Yuma Omori[1(✉)], Hideaki Kawano[1], Akinori Seo[1], Zohreh Gholami Doborjeh[2], Nikola Kasabov[2], and Maryam Gholami Doborjeh[2]

[1] Kyushu Insititute of Techonology, Kitakyushu 804-8550, Japan
omori.yuma780@mail.kyutech.jp, kawano@ecs.kyutech.ac.jp
[2] Knowledge Engineering and Discovery Research Institute, Auckland University of Technology, Auckland 1142, New Zealand
zohreh.gholamidoborjeh@aut.ac.nz

Abstract. This paper is a feasibility study of using the NeuCube spiking neural network (SNN) architecture for modeling EEG brain data related to perceiving versus mimicking facial expressions. We collected EEG patterns during perception and imitation of facial expressions for each emotion. Comparing the collected data in perceiving and mimicking facial expressions, EEG patterns were very similar. This fact suggests that it seems that there are mirror neurons on facial expression in the human brain. Recently, some studies have been reported that the mirror neuron system does not work well in the case of subjects with brain disorders. In this study, we calculated differences between EEG patterns when we perceived facial expressions and mimicking facial expressions for healthy people and developmental disorders.

Keywords: EEG data · SNN · Mirror neuron system · Developmental disorders

1 Introduction

Facial expression is a fundamental tool in human communication. Understanding the facial expression effects on a third person is of a crucial importance to develop a comprehensive communication. Neuropsychological studies reported that communications through facial expressions are highly related to the Mirror Neuron System (MNS). MNS principle has been introduced in 1990s by Rizzolatti when he discovered similar areas of the brain became activated when a monkey performed an action and when a monkey observed the same action performed by another [1]. The MNS in human were also confirmed by an experiment using functional magnetic resonance imaging (fMRI) data [2]. Different facial expressions of emotion have different effects on the human brain activity.

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The brain processes of perceiving an emotional facial expression and mimicking expression of the same emotion are spatio-temporal processes. The analysis of collecting Spatio-Temporal Brain Data (STBD) related to these processes could reveal personal characteristics or abnormalities that would lead to a better understanding of the brain processes related to the MNS. This can be achieved only if the models created from the STBD can capture both spatio and temporal components from this data. Despite of the rich literature on the problem, such models still do not exist.

Recently, a brain-inspired Spiking Neural Network (SNN) architecture, called NeuCube [4–6], has been proposed to capture both the time and the space characteristics of STBD, such as EEG, fMRI, DTI, etc. In contrast to traditional statistical analysis methods that deal with static vector-based data, the NeuCube has been successfully shown to be a rich platform for STBD mapping, learning, classification and visualization [7–9].

In this paper, we examined differences in brain activity patterns between healthy people and developmental disabilities by calculating the difference EEG data of facial expression task (both perceiving and mimicking) in two kinds of emotional faces (anger, happiness). The models allow for a detail understanding on the problem.

2 The NeuCube Spiking Neural Network Architecture

The NeuCube architecture [4] consists of: an input encoding module; a 3D recurrent SNN reservoir/cube (SNNc); an evolving SNN classifier. The encoding module converts continuous data streams into discrete spike trains. As one implementation, a Threshold Based Representation (TBR) algorithm is used for encoding. The NeuCube is trained in two learning stages. The first stage is unsupervised learning based on spike-timing-dependent synaptic plasticity (STDP) learning [10] in the SNNc. The STDP learning is applied to adjust the connection weights in the SNNc according to the spatiotemporal relations between input data variables. The second stage is a supervised learning that aims at learning the class information associated with each training sample. The dynamic evolving SNNs (deSNNs) [11] is employed as an output classifier. In this study, the NeuCube is used for modeling and learning of the case study EEG data corresponding to different facial expressions.

3 The Case Study STBD: EEG Data Evoked by Facial Expression

The subjects were 11 Japanese adult males, 10 healthy person and 1 development disabled in the case study of the facial expression task. As facial stimuli, JACFEE collection [12] was used, consisting of 56 color photographs of 56 different individuals. Each individual illustrates one of the two different emotions, i.e. anger, happiness. The collection is equally divided into male and female populations (28 males, 28 females).

During the experiments, subjects were wearing an EEG headset (Emotive EPOC+) which consists of 14 electrodes with the sampling rate of 128 Hz and the bandwidth is between 0.2 and 45 Hz.

The EEG data was recorded while the subjects were performing two different facial expression tasks. During the first presentation, subjects were instructed to perceive different facial expression images shown on a screen, and in the second presentation they were asked to mimic the facial expression images. We used five patterns of facial expression images per emotion in these experiments.

Each facial expression image was exposed for 5 s followed by randomly 5 to 10 s inter stimulus interval (ISI) as shown in Fig. 1.

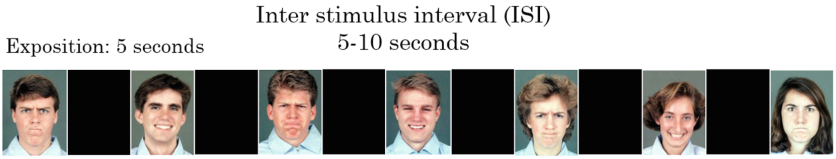

Fig. 1. The facial expression-related task: the order of emotion expressions is alternation of anger and happiness. Each subject watched 10 images during an experiment.

4 Analysis of the Spatiotemporal Connectivity in a Trained SNNc of a NeuCube Model

A 3D brain-like SNNc is created to map the Talairach brain template of 1471 spiking neurons [13,14]. The spatio-temporal data of EEG channels were encoded into spike trains and entered to the SNNc via 14 input neurons which spatial locations in the SNNc correspond to the 10–20 system location of the same channels on the scalp. The SNNc is initialized with the use of the "small world" connectivity [4].

We input EEG data obtained from five patterns of facial expressions images into one SNNc, and created a model for each subject. Table 1 shows that NeuCube parameter values used in the simulations.

Table 1. NeuCube parameter values used in the simulations.

Parameter	Value
TBR	0.5
Small world connectivity distance	2.5
STDP rate	0.01
Training iteration	1
Training time length	0.2

During the unsupervised STDP learning, the SNNc connectivity evolves with respect to the spike transmission between neurons. Stronger neuronal connection between two neurons means stronger information (spikes) exchanged between them.

Table 2 shows the numerical differences of EEG data between imitation and perception in 2 facial expressions (ANGRY and HAPPY) from each subject. The definitions of the L1-difference D_{L1} and the L2-difference D_{L2} are shown in Eqs. (1) and (2).

$$D_{L1} = \sum_{i}^{N} |w_i^{perceiving} - w_i^{mimicking}|, \tag{1}$$

$$D_{L2} = \sum_{i}^{N} (w_i^{perceiving} - w_i^{mimicking})^2, \tag{2}$$

where w_i represents weight parameter between neurons in SNNc.

Table 2. The difference between facial expressions (perceiving and mimicking) of 2 kinds of emotion (Angry and Happy).

Subject	D_{L1}		D_{L2}	
	ANGRY	HAPPY	ANGRY	HAPPY
A (Developmental disorder)	1897.8	1894.9	86.2	86.2
B (healthy)	1889.8	1880.9	85.6	85.2
C (healthy)	1890.7	1881.8	85.4	85.2
D (healthy)	1893.3	1874.1	85.5	84.5
E (healthy)	1888.7	1884.9	85.9	84.8
F (healthy)	1888.6	1881.4	85.1	85.4
G (healthy)	1885.4	1875.8	85.1	84.7
H (healthy)	1886.1	1892.4	85.2	85.4
I (healthy)	1886.1	1886.9	85.2	85.6
J (healthy)	1879.8	1872.9	84.6	84.5
K (healthy)	1890.5	1894.2	85.9	85.7
AVG of healthy	1887.9	1882.5	85.5	85.1
STDDV of healthy	3.75	7.24	0.39	0.45

As shown in Table 2, the difference in the developmental disorder is higher than the one in the healthy subjects. Especially, L1-difference in ANGRY and L2-difference in HAPPY show a significant difference between a developmental disorder and healthy subjects. Indeed the number of samples in the experiment is quite small, but we believe that this fact implicates a possibility to use the difference between weight connections learnt by the NeuCube as an index to evaluate a kind of social ability.

5 Conclusion

In this paper, we used the NeuCube architecture of SNN [4] for mapping and learning of EEG data recorded from subjects when they were performing a facial expression-related task. From Table 2, it was found that the person with developmental disability has a larger difference between EEG data of perception and imitation than healthy people. This finding can prove the principle of the mirror neurons in the human brain. This is only the first study in this respect. Further studies will require more subject data to be collected for a more models developed before the proposed method is used for cognitive studies and medical practice.

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