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NEUROCOMPUTING-BASED SIMILARITY ANALYSIS OF EEG IN PERCEIVING AND MIMICKING FACIAL EXPRESSIONS

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Abstract. *By using a neuromorphic computation, mirror neuron activities on facial expressions were examined. EEG data are collected during perceiving and mimicking different facial expressions corresponding to different emotions. As a result of neural computational visualization, an EEG in perceiving a particular facial expression and an EEG in mimicking the same facial expression with respect to a particular subject were quite similar. This fact suggests that a human mirror neuron system concerning a facial expression exists in each subject. Recently, some studies have reported that the mirror neuron system does not work well in the case of subjects with brain disorders. The study is indeed based on the well-known mirror neuron concept in the brain, but this is the first attempt to analyze and visualize similarities and differences as a neurocomputing based model.*

Keywords: Mirror neuron system, Facial expression, EEG, Neurocomputing

1. **Introduction.** In the present situation, it is said to be difficult to diagnose developmental disorders including autism spectrum disorders (ASD). This fact makes it more difficult to discover the developmental disorders. If we could detect the brain disorders at an early stage, it would bring positive impacts on children's growth by appropriate treatment and education to the person. On the other hand, it is known that defects of mirror neuron system (MNS) and the ASD are highly related. The children with ASD have a relatively low activity of the mirror neuron area during imitation of facial expressions [1]. In consideration of the previous studies, we propose an evaluation system of mirror neuron activities based on facial expression. Originally, 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 [2]. The MNS in human was also confirmed by an experiment using functional magnetic resonance imaging (fMRI) data [3]. Different facial expressions of emotion have different effects on human brain activity. The brain processes of perceiving an emotional facial expression and mimicking an expression of the same emotion are spatio-temporal processes. The analysis of collected 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 electroencephalogram (EEG), fMRI, and diffusion tensor imaging (DTI). 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]. There is still not the way to visualize brain activities from brain wave that it can acquired data easily compared to other methods.

In this paper, the NeuCube was used to model EEG data of healthy subject recorded during a facial expression task (both perceiving and mimicking) to investigate the brain activity patterns elicited from 7 kinds of emotional faces (anger, contempt, disgust, fear, happiness, sadness, and surprise) in terms of similarity and differences. The models allow for a detailed understanding on the problem.

The outline of this paper is as follows. The NeuCube spiking neural network architecture is introduced in Section 2. The case study STBD using EEG data from facial expressions is described in Section 3. The analysis of the spatiotemporal connectivity in a trained NeuCube model is presented in Section 4. Finally, conclusions are drawn in Section 5.

2. **The NeuCube Spiking Neural Network Architecture.** The NeuCube architecture as shown in Figure 1 [4] consists of an input encoding module, a 3D recurrent SNN reservoir/cube (SNNc), and 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 adjusting 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 modelling, learning, and visualization of the case study using EEG data corresponding to different facial expressions.

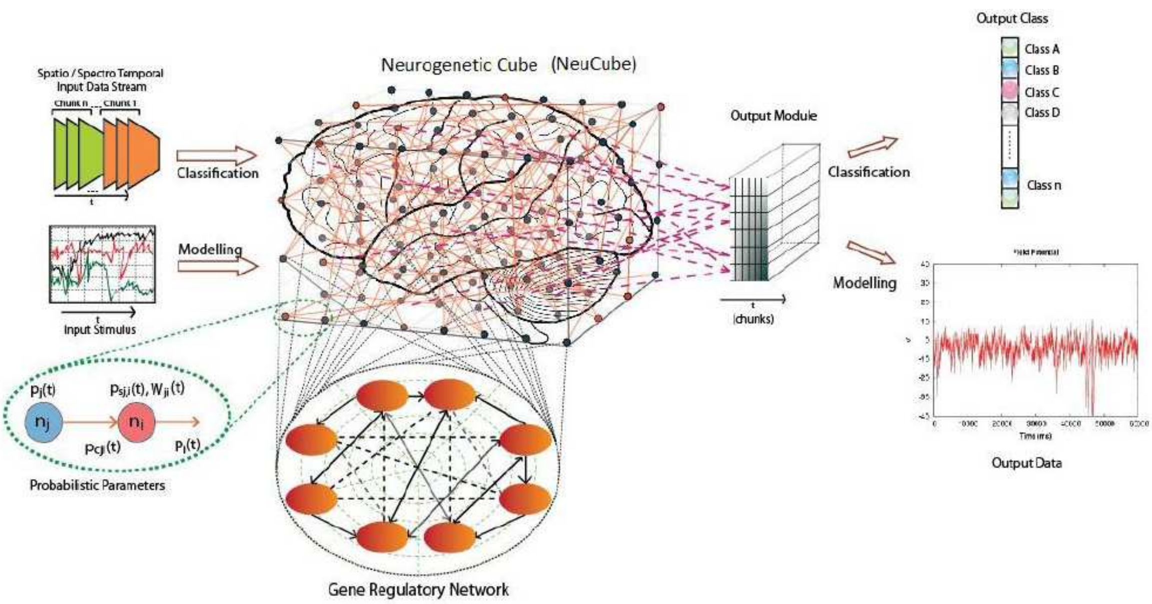


Figure 1. The NeuCube architecture

3. **The Case Study STBD: EEG Data from Facial Expressions.** Eleven male Japanese subjects aged between 22 and 25 years old ($\mu = 23.2$, $\sigma = 1.2$), participated in the case study of the facial expression task. As facial stimuli, JACFEE collection [12] was used, consisting of 56 colour photographs of 56 different individuals. Each individual illustrates one of the seven different emotions, i.e., anger, contempt, disgust, fear, happiness, sadness, and surprise. The collection is equally divided into male and female populations

(28 males, 28 females). The aim of experiment in this study is to confirm reproduction of mirror neuron activities in the NeuCube visualization framework. To this end, several healthy subjects who are expected to pose typical brain activities are corrected.

During the experiments, subjects were wearing 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 expr ession 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.

Each facial expression image was exposed for 5 seconds followed by random 5 to 10 seconds of interstimulus interval (ISI) as shown in Figure 2.

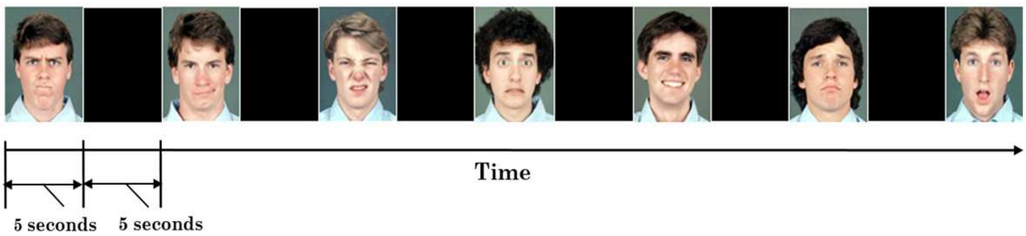


Figure 2. The facial expression-related task: the order of emotion expressions is: anger, contempt, disgust, fear, happiness, sadness, and surprise. Each subject watched 56 images during an experiment.

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 as shown in Figure 3 [13,14]. The spatiotemporal 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 sculp. The SNNc is initialized with the use of the "small world" connectivity [4].

The following NeuCube parameter values were used in the simulations: TBR: 0.5, small word connectivity distance: 2.5, and STDP rate: 0.01. 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. For example, in the training process of SNNc, the weight connectivity changes as shown in Figure 4. Figure 5 illustrates the trained SNNc with EEG data of perceiving and mimicking different facial expressions. It also shows the differences between the SNNc connectivity of perceiving versus mimicking, which was obtained after the two corresponding models were subtracted. It can be seen from Figure 5 that when an SNNc was trained on the EEG data related to facial expressions of both perceiving and mimicking conditions, similar neuronal connections were evoked in the SNNc reflecting similar cortical activities. Particularly, greater similarity can be observed in the right hemisphere of the SNNc for anger, contempt, sadness, and surprise. This finding proves a neurological fact that this emotional information is usually processed across specific domains of the right hemisphere of the brain [15]. It also reflects the MNS principle in facial expression of emotion. Among all the presented emotional faces, some of them can be considered as dominant emotions if the brain activity patterns of perceiving and mimicking of emotions have a high level of similarity. This similarity is mostly observed for sadness.

Figure 6 shows a comparison result between the weight connectivity obtained from anger-face-mimicking task and one obtained from happy-face-perceiving task with respect

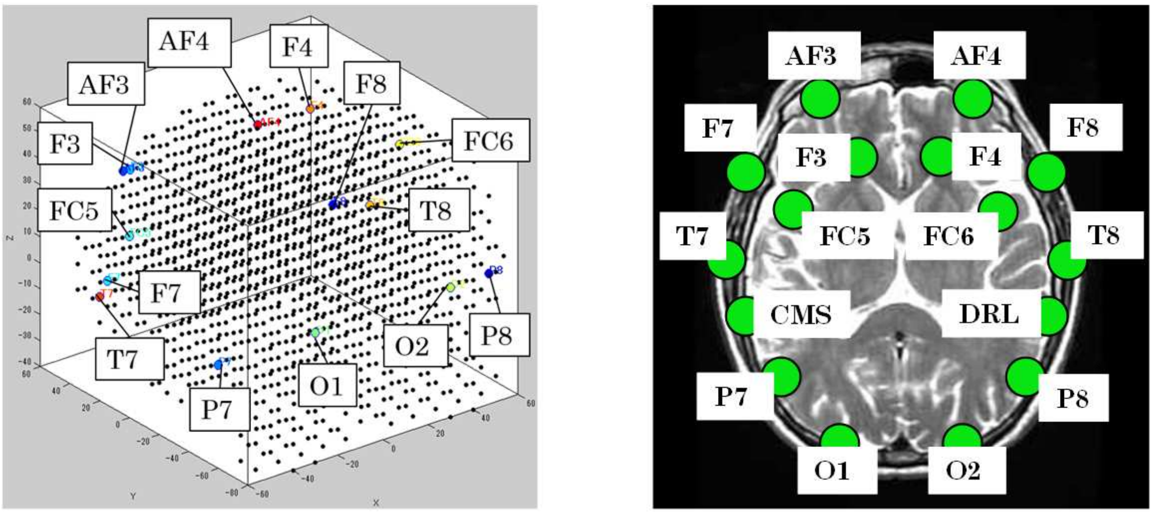
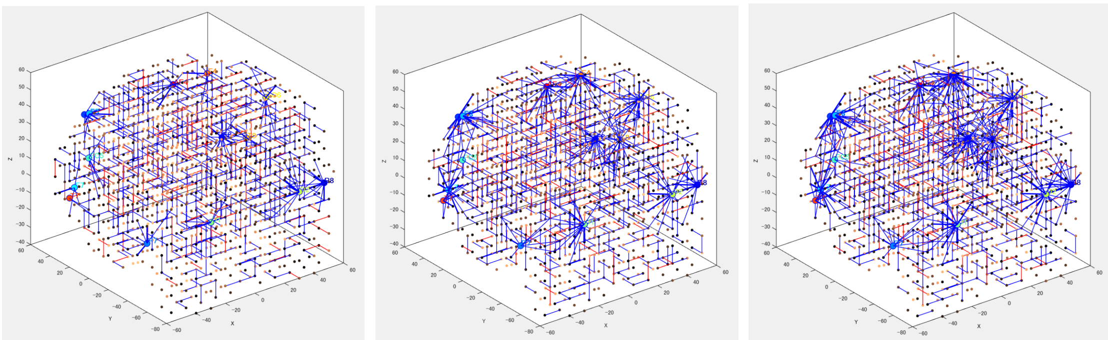


FIGURE 3. The relationship between NeuCube SNNc and Talairach brain template



Initial State 0 times | Middle State 5 times | Final State 10 times

FIGURE 4. A training process of SNNc

to subject A. As we can see from Figure 5(c), connectivity between the same emotion tasks is quite similar; on the other hand, as we can see from Figure 6(c), connectivity among different emotion tasks is not similar. Much the same is true of comparisons with other emotions. Figure 7 shows comparison results between the weight connectivity obtained from subject A's mimicking task and other subject B's perceiving task with respect to anger emotion. As we can see from Figure 5(c), connectivity between the same subject tasks is quite similar; on the other hand, as we can see from Figure 7(c), connectivity among the different subject tasks is not similar. Therefore, the degree of mirror neuron activity should be examined for every subject and every emotion.

5. **Conclusions.** In this paper we used the NeuCube architecture of SNN [4] for mapping, learning and visualization of EEG data recorded from subjects when they were performing a facial expression-related task. We observed similar spatiotemporal connectivity created in the SNNc trained by the EEG data of perceiving a particular facial expression versus mimicking the same facial expression. This finding can prove the principle of the mirror neurons in human brain.

According to the experiment, the degree of mirror neuron activity should be examined for every subject and every emotion.

This is only the first study in this respect. Further studies will require more subject data to be collected for more models developed before the proposed method is used for cognitive studies and medical practice.

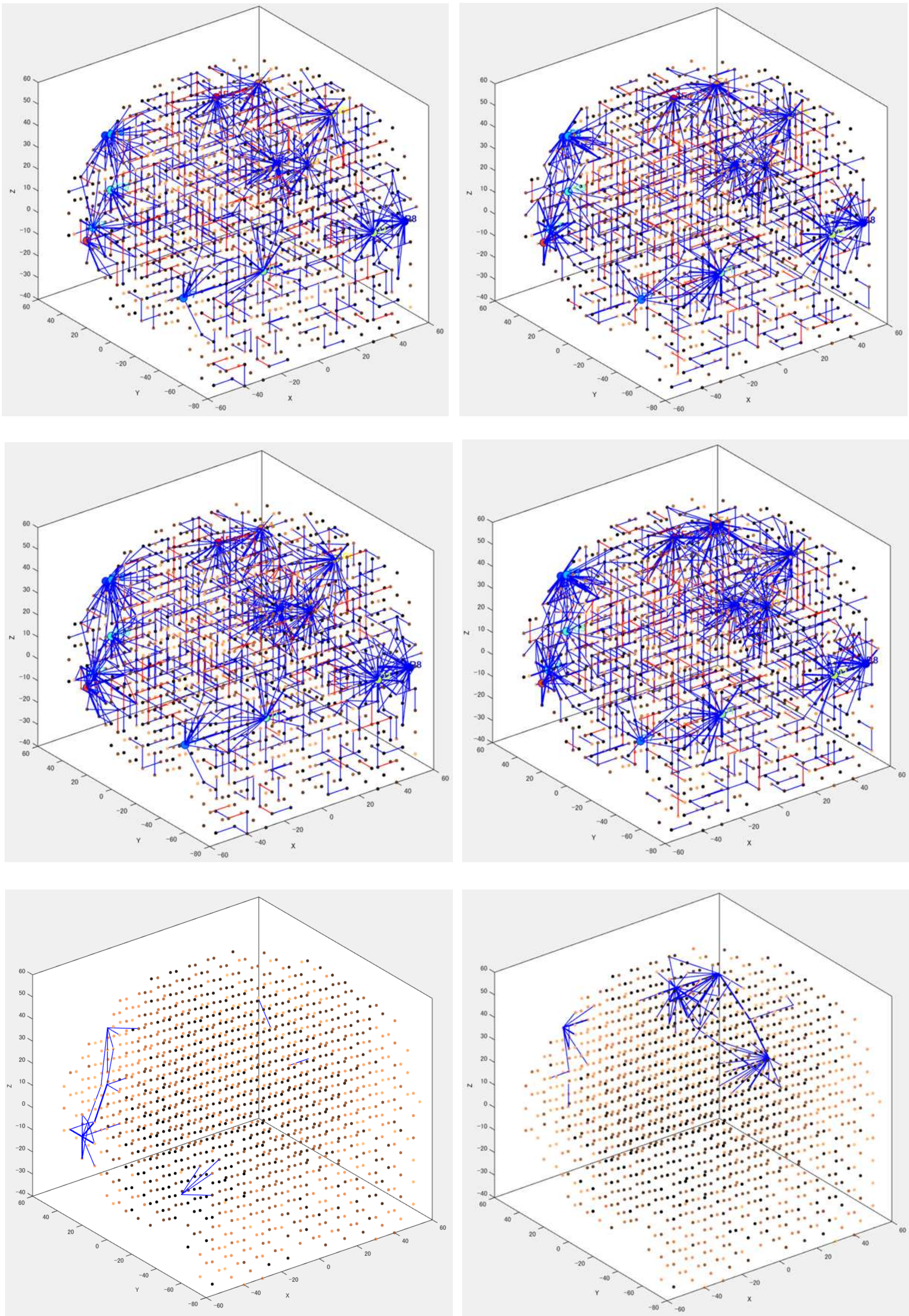


Figure 5. (a) Connectivity of an SNNc trained on EEG data related to mimicking the facial expression of anger and happiness, (b) connectivity of an SNNc trained on EEG data related to perceiving the facial expression of anger and happiness, (c) subtraction of the SNNc models from (a) and (b) to visualize, study and understand differences between perceiving and mimicking emotion

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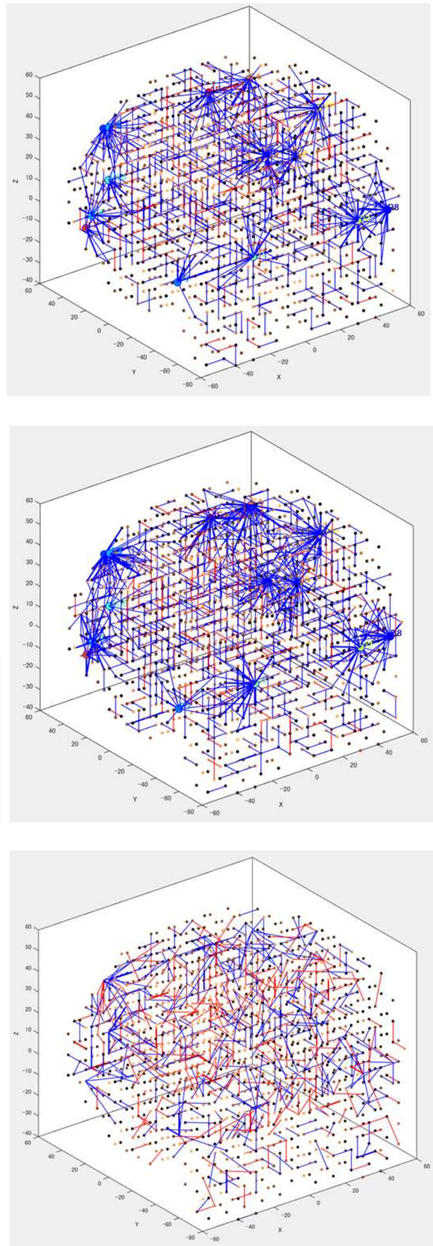
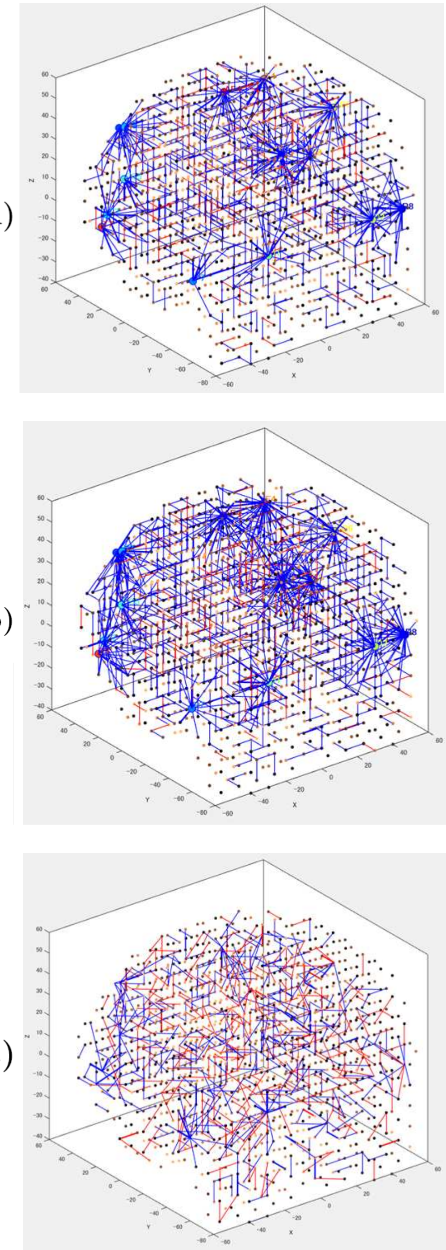


(a)

(b)

(c)

Figure 6. (a) Connectivity of an SNNc trained on EEG data related to mimicking the facial expression of anger by subject A, (b) connectivity of an SNNc trained on EEG data related to perceiving the facial expression of happiness by subject A, (c) subtraction of the SNNc models from (a) and (b) to visualize, study and understand differences between perceiving and mimicking emotions



(a)

(b)

(c)

Figure 7. (a) Connectivity of an SNNc trained on EEG data related to mimicking the facial expression of anger by subject A, (b) connectivity of an SNNc trained on EEG data related to perceiving the facial expression of anger by subject B, (c) subtraction of the SNNc models from (a) and (b) to visualize, study and understand differences between perceiving and mimicking emotions

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