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사이버멀미 발생 예측을 위한 대뇌 구조를 반영한 CNN 성능 분석

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Analyses on the Performance of the CNN Reflecting the Cerebral Structure for Prediction of Cybersickness Occurrence

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요 약 본 논문에서는 사이버 멀미 발생 예측에 활용 할 CNN 기반의 신경망의 성능 향상을 위하여, 다양한 형태의 신경망 구조에 대한 성능 분석을 수행한다. 특히, 대뇌 구조의 특성을 반영한 CNN을 차별적으로 구현하여 각 CNN(Convolution Neural Network)의 성능을 비교 분석하였으며, 이를 기반으로 사이버 멀미 발생 예측에 최적화된 신경망 구조의 설계와 관련한 기본적인 이론을 제시한다. 사이버 멀미 발생에는 많은 원인이 있지만 가장 중요한 원인은 뇌와 관련된 전정 기능의 장애에 기인한 것으로 판단된다. 뇌파는 뇌 활동 상태를 나타내는 지표 역할을 하며 외부 자극과 뇌 활동에 따라 차이를 나타낸다. 2019년에 출판된 Tony Ro의 Martijn E. Wokke 논문을 포함한 많은 연구와 실험에 의해 외부 자극과 뇌 활동으로 인한 뇌파의 변화가 입증되었으며, 본 논문에서는 이러한 상관관계를 바탕으로 사이버 멀미 유발 환경에서 수집 한 뇌파 데이터를 분석하고 뇌 구조의 특성을 반영하는 사이버 멀미 예측 인공 신경망의 구현 가능성을 제시하였다. 본 연구의 결과는 사이버 멀미 예측에 활용되는 CNN의 최적 성능 도출을 위하여, 고려하여야 할 신경망의 기본 구조 설계에 활용될 수 있으며, 다양한 가상현실(VR) 환경 등 대뇌 활동이 관여하는 분야에서 응용 될 신경망 구조 설계의 기초를 제공 할 것으로 기대된다.

• 주제어 : 신경망 구조, 사이버 멀미, 뇌파, 대뇌 구조, 인공신경망

Abstract In this study, we compared and analyzed the performance of each Convolution Neural Network (CNN) by implementing the CNN that reflected the characteristics of the cerebral structure, in order to analyze the CNN that was used for the prediction of cybersickness, and provided the performance varying depending on characteristics of the brain. Dizziness has many causes, but the most severe symptoms are considered attributable to vestibular dysfunction associated with the brain. Brain waves serve as indicators showing the state of brain activities, and tend to exhibit differences depending on external stimulation and cerebral activities. Changes in brain waves being caused by external stimuli and cerebral activities have been proved by many studies and experiments, including the thesis of Martijn E. Wokke, Tony Ro, published in 2019. Based on such correlation, we analyzed brain wave data collected from dizziness-inducing environments and implemented the dizziness predictive artificial neural network reflecting characteristics of the cerebral structure. The results of this study are expected to provide a basis for achieving optimal performance of the CNN used in the prediction of dizziness, and for predicting and preventing the occurrence of dizziness under various virtual reality (VR) environments.

• Key Words : Cybersickness, Dizziness, CNN, EEG, Artificial Neural Network

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Ⅰ. Introduction

Currently, much research related to the brain has been conducted, and significant progress has been reported by studies that have investigated brain waves. Brain waves refer to the flow of electricity generated when signals are transmitted between the nerves in the nervous system, which varies, depending on the state of mind and body, and serve as an indicator measuring brain activities [2]. Brain waves differ, depending on external stimuli by individuals, and the specific nature of their cerebral activities, and this has been proven in many studies and experiments. Moreover, brain waves change according to the presence of physical and mental diseases and the psychological state of a person, which is the same case where the dizziness is felt [3]. The brain integrates and analyzes the sensory information received, through the various senses, and the vestibular system, so as to balance the body. Therefore, in situations which cause abnormalities in the sensory nervous system or the central nervous system that accepts information, dizziness may be caused by various factors, such as internal diseases and psychological abnormalities, etc., when blood supply to the brain is inadequate, due to overwork, stress, abnormalities in the area from the ear to the brain, and heart problems [4]. Various types of artificial neural network structures were designed for performance analyses according to the cerebral region when the data on brain waves were investigated. That is attributed to the characteristics of the brain generating different brain waves, depending on the area, and to the correlation manifested according to the route of the area where the brain waves pass, i.e., the two different functional routes of the human cerebral cortex, classified into the occipital, parietal, and frontal lobes, which process spatial information, as well as visual information [5-8]. In this study, therefore, we implemented artificial neural networks of various types by reflecting the cerebral structure as illustrated in Fig. 1 below based on the neural networks involving brain waves as the input signal, and particularly, applied the CNN structure, a type of artificial neural network.

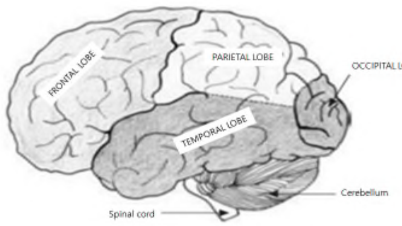

Fig. 1. Cerebral structure

Ⅱ. Experiment Design

In this study, the experiment was performed with a total of 56 healthy men and women enrolled as subjects. The subject group consisted of 28 men and 28 women. Before the start of the dizziness-inducing experiments, subjects were checked for their visual acuity and presence of disease. Only subjects with visual acuity of at least 0.1, a level which caused no problem in viewing a video, were allowed to participate in the experiment. Subjects who participated in the experiment watched a video designed to induce dizziness by using an augmented reality (AR) environment (EPSON MOVERIO BT-350) built in this laboratory. For data collection, the background brain waves of subjects were measured for 30 minutes in a steady state before exposing them to an AR environment, wherein they watched a dizziness-inducing video, and then their brain waves were measured for 15 minutes during this period of dizziness. When dizziness occurred during the measurement of brain waves in a dizziness-induced state, the brain wave data were collected for 1 minute from the time of the occurrence of dizziness, and then the experiment ended. If subjects did not sense any dizziness, the experiment was finished after they watched the entire 15-minute video. As 36 out of 56 subjects sensed dizziness, only the data collected from the 36 subjects were used for analysis.

Fig. 2 below shows the structure when cybersickness did not occur during the dizziness-inducing experiment. By contrast, Fig 3 shows the structure when cybersickness did occur.

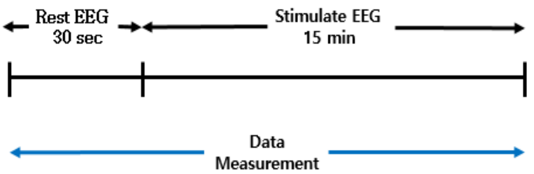

Fig. 2. No cybersickness occurred within 15minutes

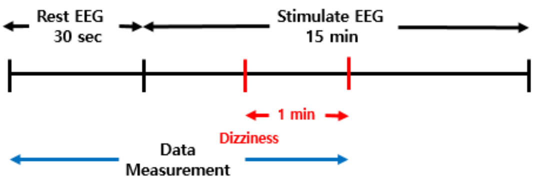

Fig. 3. Cybersickness occurred within 15 minutes

Ⅲ. Design of the Artificial Neural Network

3.1 Basic Structure of the Neural Network

The basic structure of the artificial neural network, was designed to predict when dizziness would occur, based on the data collected in the dizziness-inducing experiment, is explained below.

The neural network algorithm used in this study was the CNN algorithm. For the input value, the value that quantified brain wave signals was visualized. The width of the image was processed by the FFT (Fast Fourier Transform) after sampling the brain waves of subjects at 250Hz. And the energy value in the band of frequency between 0Hz and 50Hz, which contained information about brain waves among the signals obtained as the result value, was used as the width of the image. The height of the image was set to 1 because the input signal was analyzed based on frequency characteristics by seconds. Meanwhile, the depth of the image was set to 32 because the brain wave measuring device of 32Channel was used in this experiment. When the image was added into the input layer, the convolution was performed by using 30 filters, each measuring 30 ×1. When the convolution calculation was performed by defining the stride value as 1, a total of 21 feature maps were calculated.

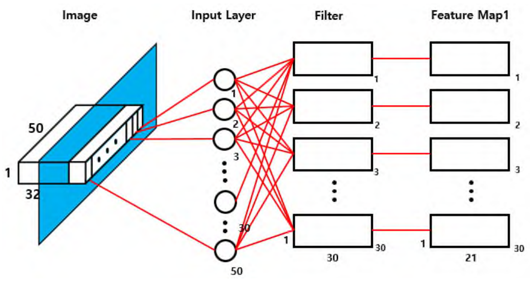

Fig. 4. Input node and first convolution layer

When the first convolution was completed, feature maps with a size of 21 × 1 were generated by as many as the number of “Depth (32) × Filters (30)”, and those feature maps were pooled, and at this time, the Max Pooling technique was applied. Pooling proceeded with a size of 10 × 1, and the stride was set first to 2. After pooling, the feature map was reduced to 6 × 1 size. The second convolution was performed by using the reduced feature maps as the input data. In the second convolution, 3 filters, each with a size of 6 ×1, were used.

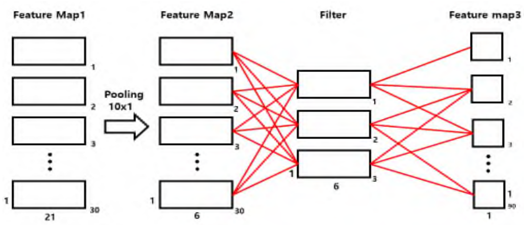

Fig. 5. Pooling process an second convolution layer

When proceeding with the second convolution, a value with a size of 1 × 1 was generated by as many as [Depth (32)× quantity of Filter (30, First

Convolution) × quantity of filters (3, Second Convolution)], and the nodes were connected to the Fully Connected Layer to classify the output value. In this study, the number of nodes to be connected to the Fully Connected Layer was defined as 3,000, given that it was found to be the quantity of nodes showing the highest predicted 'result value' based on the outcome of continuous learning. The 3,000 nodes of the Fully Connected Layer were connected to the 11 output layer nodes for the classification.

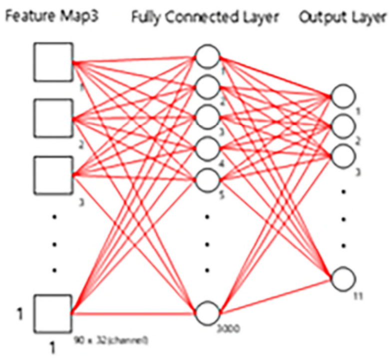

Fig. 6. Fully connected layer and Output layer

The In-Out values, which had respective layers used in this study, are presented in Table 1 below. Table 1. Input and output of the artificial neural network.

Table 1. Input and output of the artificial neural network

Name	In	Out
Input	(50, 1, 32)	(50, 1, 32)
Convolution 1	(50, 1, 32)	(21, 1, 32x30)
Pooling	(21, 1, 32x30)	(6, 1, 32x30)
Convolution 2	(6, 1, 32x30)	(1, 1, 32x30x3)
Fully Connected	(1, 1, 32x30x3)	3000
Output	3000	11

The rules applied to the learning of the artificial neural network in this study are presented in Table 2.

Table 2. Training environment setting

Training environment setting	
Loss Function	Cross Entropy
Activation Function	ReLU Softmax
Learning Rate	0.001
Training Step	1,000,000

The loss function of CNN used in this study was the Cross_Entropy function. For the activation function, we used the ReLU and Softmax. The learning rate was set to 0.001 and the training step was set to 1,000,000 when the learning was conducted.

3.2 Neural Network Reflecting the Cerebral Structure

In this study the neural network was modified to reflect the characteristics of the cerebral structure, and for that, the neural network structure was altered by changing the depth value of the input node.

3.2.1 Depth Structure Neural Network Based on The Measuring Equipment Channel

The first neural network designed in this study applied the method of arrangement in the depth according to the order of the channels provided by the brain wave measuring equipment, as shown in Fig. 7 below.

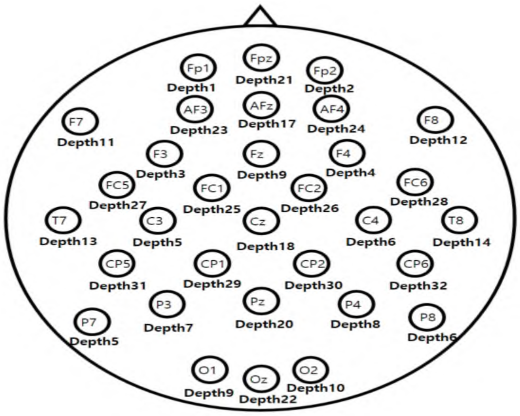

Fig. 7. Design based on the measuring equipment

3.2.2 Depth Structured Neural Network Based on Left and Right Cerebral Hemispheres

For the second neural network designed in this study, the measurement was performed separately for the left and right hemispheres based on the channel of the measuring equipment, as illustrated in Fig. 8 below. The value of the left hemisphere was placed before the Depth, while the value of the right hemisphere was placed after the Depth.

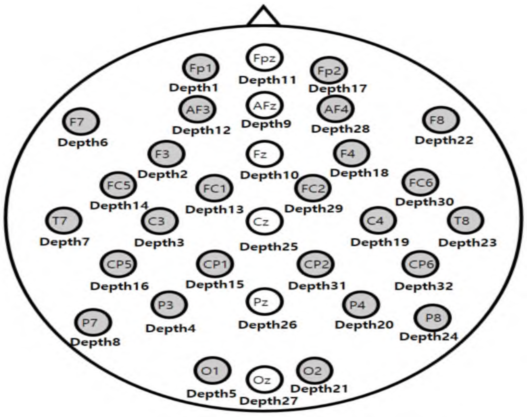

Fig. 8. Design based on the left and right cerebral hemispheres

3.2.3 Depth Structural Neural Network Based on 5 Cerebral Lobes

The third neural network designed in this study was based on the cerebral structural region, not the channel of the measuring equipment, while the cerebral structural region was divided into the left and right hemispheres, as shown in Fig. 9 below. Regarding the order of depth, the frontal, temporal, parietal, and occipital lobes of the left hemisphere were arranged first. Then, the corresponding lobes of the right hemisphere were arranged. Finally, a channel in the cerebral centerline was arranged.

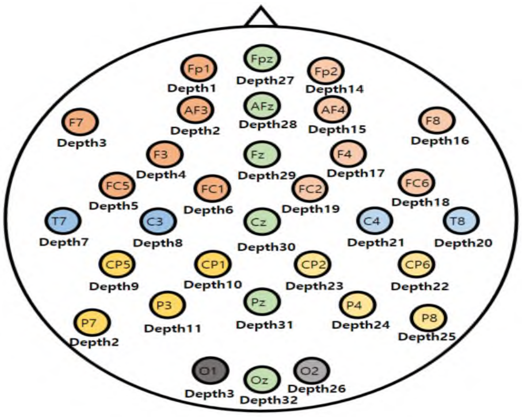

Fig. 9. Design based on cerebral region structure

Table 3. Depths and channels of CNN

Depth	Montage	Type 1 Channel	Type 2 Channel	Type 3 Channel
Depth1	Fp1	1	1	1
Depth2	Fp2	2	17	14
Depth3	F3	3	2	4
Depth4	F4	4	18	17
Depth5	C3	5	3	8
Depth6	C4	6	19	21
Depth7	P3	7	4	11
Depth8	P4	8	20	24
Depth9	O1	9	5	13
Depth10	O2	10	21	26
Depth11	F7	11	6	3
Depth12	F8	12	22	16
Depth13	T7	13	7	7
Depth14	T8	14	23	20
Depth15	P7	15	8	12
Depth16	P8	16	24	25
Depth17	Afz	17	9	28
Depth18	Cz	18	25	30
Depth19	Fz	19	10	29
Depth20	Pz	20	26	31
Depth21	Fpz	21	11	27
Depth22	Oz	22	27	32
Depth23	AF3	23	12	2
Depth24	AF4	24	28	15
Depth25	FC1	25	13	6
Depth26	FC2	26	29	19
Depth27	FC5	27	14	5
Depth28	FC6	28	30	18
Depth29	CP1	29	15	10
Depth30	CP2	30	31	23
Depth31	CP5	31	16	9
Depth32	CP6	32	32	22

Ⅳ. Results of Experiment

The results of the 3 types of neural networks, designed in the neural network reflecting the cerebral structure, were as follows: The first method involved arrangement of Depth based on the channel of the measuring equipment. The results of the Depth Structure Neural Network based on measurement equipment channels turned out to be equal to 86.00% accuracy based on 1,000,000 steps. Fig. 10 below is a graphical representation of the results. The X-axis shows the step number and the Y-axis shows the accuracy value.

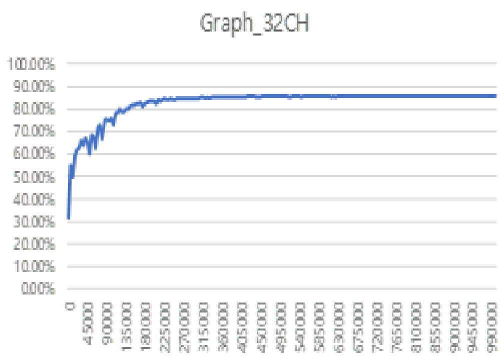

Fig. 10. Results of the Depth Structure Neural Network based on the channel of measuring equipment

The second method involved division of the brain into left and right hemispheres on the cerebral centerline, which was followed by the arrangement of the left hemisphere in front of the Depth and arrangement of right hemisphere behind the Depth according to the order of channels of the measuring equipment. The learning result of the Depth Structural Neural Network based on the left and right cerebral hemisphere was found to be equal to 69.22% accuracy based on 1,000,000 steps. Fig. 11 below is a graphical representation of the results.

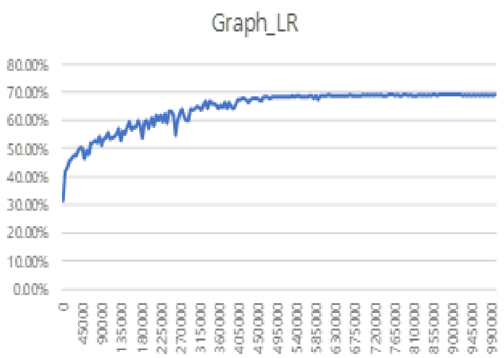

Fig. 11. Results of Depth Structural Neural Network based on the left and right cerebral hemispheres

The third method involved the arrangement of the Depth first by the left hemisphere cerebral region based on the cerebral centerline, followed by the arrangement of the Depth in the right hemisphere cerebral region. Finally, the channel at the centerline of the cerebral structure was arranged in Depth. The results of Depth structure neural network based on cerebral 5 lobes was found to be equal to 85.59% accuracy based on 1,000,000 steps. Figure 12 below is a graphical representation of the results.

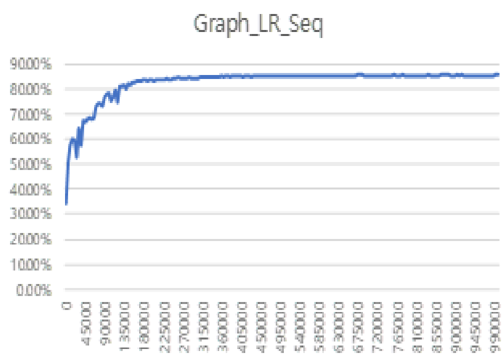

Fig. 12. Results of the Depth Structure Neural Network based on the 5 cerebral lobes

Ⅴ. Results

In this study, we analyzed the performance of dizziness predictive CNN that reflected the characteristics of the cerebral structure. A dizziness-inducing experiment was carried out and the data on brain waves were collected while the dizziness was being induced. Based on the collected data, it was found that the performance of neural networks varied, depending on the characteristics of the cerebral structure.

The structure of the neural network reflecting the characteristics of the cerebrum may be variously reflected depending on the viewpoint of the cerebrum. However, in this paper, only two forms reflecting basic cerebral structure characteristics were tested. The results of the experiment showed that the result value of the neural network reflecting the characteristics of the cerebral structure was superior to that of the general artificial neural network in terms of performance. In particular, it was found that there was a difference of about 15% in accuracy at the same step when the learning was conducted in the ordinary neural network by separating the left and right cerebral hemispheres and when the learning was conducted in the neural network reflecting the characteristics of the cerebral structure.

If studies are to be carried out based on the results of this study, measures will be derived which enable not only the prediction of dizziness in human beings, but also the prevention of dizziness. Additionally, if the studies continue to be conducted by applying the characteristics of the cerebral structure to neural networks, new neural networks which provide better performance than existing neural networks will be able to be developed.

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