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APPLIED RESEARCH

Effective Neurofeedback Training of Large Electroencephalogram Signals Using Serious Video Games

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ABSTRACT Neurofeedback can be utilized to treat various neuropsychiatric disorders in children. However, therapists primarily set threshold values for neurofeedback training. Thus, the training effect becomes subjective owing to the experience of the therapist. A clinically inexperienced therapist could set inappropriate thresholds, rendering the training ineffective. In this study, an effective neurofeedback system that includes signal processing of large amount of electroencephalogram (EEG) data and auto thresholding and provides various training contents was developed. The system uses a method that determines optimal threshold values, which are significant for an effective neurofeedback system. The success or failure of the activation and inhibition of specific EEG frequencies was determined based on these threshold values. The system determined an optimal threshold value to obtain the target success rate using a numerical optimization technique. The success or failure feedback for the reward and inhibit EEG frequencies was generated using auto thresholding. This feedback was sent to the training contents by the inter-process communication module to control the contents. Most training content was implemented as serious video games by using a commercial game engine. Success feedback on reward EEG frequency leads to game progress. By contrast, failure feedback on inhibiting EEG frequency hinders game progress. Consequently, the user gains the self-regulation ability to enhance the reward EEG frequency and suppress the inhibit EEG frequency. A pilot study involving five children with attention deficiency was conducted to demonstrate the effectiveness of the developed system. The results demonstrated that the childrent's attention improved after neurofeedback training.

INDEX TERMS Neurofeedback, biofeedback, comprehensive attention test (CAT), attention deficit hyperactivity disorder (ADHD), auto thresholding, serious video game.

I. INTRODUCTION

The recent convergence of brain science with information communication technology has resulted in the development of novel technologies such as neuroinformatics and brain-computer interaction (BCI). An important representative of this convergence is biofeedback therapy, often referred to as biofeedback. In biofeedback, biosignals are converted into perceivable information played as feedback to the subject over visual, auditory, haptic, or other interfaces. Such

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information helps subjects be aware of their physiological signals and consequently improve the self-regulation ability of the corresponding physiological functions.

Electroencephalogram (EEG) is an important biosignal widely used in various applications. Anwar et al. [1] used EEG to record human brain activity during gaming. They proposed a method for classifying the expertise level of a game player and argued that their method could improve the effectiveness of the educational system. Neurofeedback is a specific type of biofeedback focusing on EEG as a biosignal to promote the self-regulation of brain function. Neurofeedback can be utilized to treat neuropsychiatric disorders in children, including learning disabilities, attention deficit hyperactivity disorder (ADHD), and autism.

In neurofeedback, electrodes are placed on the head of the subject to measure brainwaves in real time. An efficient signal processing technology is required to extract the reward and the inhibit frequency signals in real time from brainwaves measured from several electrodes. When the amplitude of a reward frequency exceeds a specified threshold, successful feedback is generated, such that the subject can recognize the activation of the corresponding frequency. However, when the amplitude of an inhibit frequency exceeds a specified threshold, failure feedback is generated. As this process of activating certain EEG frequencies above the threshold and teaching the subject to recognize their brainwave state is repeated, the subject learns to actively self-regulate the desired frequencies of the brainwave. Because this technique demonstrates that the autonomous and central nervous systems can be self-regulated, it has been continuously studied as noninvasive therapy without side effects in treating or improving brain disorders [2], [3].

A neurofeedback system consists of an operating software for the therapist and training content for subjects. The operating software analyzes the power of the EEG frequencies of the subject in real time. Based on the real-time state of a subject, the thresholds of reward and inhibit frequencies are adjusted manually by the therapist, who controls the training condition of the subject. Our research is motivated from the fact that appropriate thresholds are necessary for improving the training effects. In cases where a clinically inexperienced therapist sets inappropriate thresholds, the therapy produces a relatively weak effect. Therefore, finding the optimal thresholds is vital for effective neurofeedback training. Training content is typically provided in the form of a serious video game to enable subjects to intuitively recognize their brainwave conditions.

Two issues must be considered to improve the effectiveness of neurofeedback training. First, a method to automatically calculate and adjust thresholds must be developed to minimize over-reliance on clinical expertise and the continuous presence of the therapist during a neurofeedback session. Second, creating and provisioning high-quality content must be facilitated and simplified. In this paper, we addressed these issues and developed a complete neurofeedback system that supports the these features. Contributions of this paper are as follows:

- The proposed system supports adaptive automatic thresholding for effective neurofeedback training. A numerical optimization technique to automatically calculate the thresholds is proposed to achieve the success rates designated by a therapist.
- The proposed system provides an inter-process communication (IPC) module that transmits real-time EEG analysis results to a commercial game engine to develop effective training content (video games) rapidly and conveniently.
- A pilot study involving five children with attention deficiency was conducted to demonstrate the effectiveness of the developed system. The results demonstrated that the children's attention improved after neurofeedback training.

The remainder of this paper is organized as follows. Section II discusses previous studies and relevant clinical tests on neurofeedback training. Section III presents the method used for acquiring, processing, and analyzing EEG signals. In addition, it explains the generation of success and failure feedback from EEG signals and the auto thresholding method for effective training. Section IV describes the production of various training contents and their control mechanisms depending on the success and failure feedback from the EEG signals. Section V provides pilot test results for five children with ADHD symptoms to confirm the effectiveness of the developed neurofeedback training system. Finally, Section VI concludes the paper and suggests the future work.

II. RELATED WORK

The primary premise of neurofeedback is grounded in the observation that the wavelengths of brainwaves are related to the level and type of mental activity at any given time. Berger [4] measured the brainwaves of humans for the first time in 1929. Since then, many related studies have been conducted. Nowlis and Kamiya [5] performed an experiment in which subjects were orally instructed to recognize the activity corresponding to the alpha wave. They found that the subjects were able to regulate the state of their brainwaves.

The EEG frequency bands typically used in neurofeedback are the sensorimotor rhythm (SMR) in the 12–15 Hz range, theta wave in the 4–7 Hz range, and high beta wave in the 22–36 Hz range. Wyrwicka and Sterman [6] discovered that an increase in the SMR in cats reduced the motor activity and spasms. They also showed that the specific brainwaves of a cat can be increased by operant conditioning. Sterman et al. [7] attached a sensor to the position of the somatosensory center of the cerebral cortex in each epileptic and performed neurofeedback training to strengthen SMR. The results of the training showed that the development of epilepsy decreased in four patients who were not controlled by chemical treatment. Sterman and Bowersox [8] regarded the somatosensory thalamic nuclei as the source of SMR. They demonstrated that the activation of SMR is related to quiet wakefulness, reducing the excitability of afferent and efferent nerve pathways. Lubar et al. [9] carried out training and research on neurofeedback for children with ADHD. They published the clinical result in the test of variability of attention for the theta and beta waves in the 4–8 Hz and 16–20 Hz ranges, respectively. The decrease in the theta wave and the increase in the SMR helped improve continuous performance.

Recent advances in BCI technologies have accelerated the development of neurofeedback systems [10], [11]. Various techniques using brainwaves are actively utilized in neurofeedback systems that provide communication and control functions for people with severe disabilities [12]. Furthermore, ADHD, autism, simple tic disorders, and many other mental diseases can be explained by the distortion of brainwaves and event-related potentials. Many studies have shown that neurofeedback is effective in treating and improving these diseases [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23]. However, the clinical efficacy of neurofeedback remains controversial. For a comprehensive review of this issue, we refer to a survey [24].

Although neurofeedback therapy has significant advantages and potential, it also has limitations. Neurofeedback training is not as effective as the existing medications and surgery. Moreover, acquiring high-quality content is challenging because the training content needs to be developed by both skilled and clinically experienced experts. In addition, various experimental and clinical studies must be conducted to develop stable and efficient systems. Despite these difficulties, neurofeedback training produces few side effects, and its benefits continue longer than that of medication. Neurofeedback training also helps with significant cognitive activities; thus, it can be applied in various fields. Vernon et al. [25] suggested preparing various training protocols that can provide predictable effects through continuous clinical research and technical development to maximize the effects of neurofeedback training.

There are several commercial neurofeedback systems available, such as Procomp of Thought Technology Ltd. (Canada) [26], EEGer of EEG Store (US) [27], and Bioexplorer of Cyberrevolution Inc. (US) [28]. Procomp is widely used by clinicians, supports two channels, and provides neurofeedback and biofeedback training. However, this system is difficult to operate. EEGer has been used by US clinicians extensively. It is intuitive and easy to use. However, its training content is limited. Bioexplorer supports a general purpose biofeedback system, is primarily used by developers or researchers, and includes various program build-up functions.

In neurofeedback training, the primary task is to process EEG data in real-time and effectively. The data exhibits temporal properties, and recurrent neural network (RNN) algorithms possess the capability to handle time series data and capture temporal dependencies. Previous studies have utilized RNN for tasks such as EEG classification and prediction [29]. Due to the outstanding stability, robustness, and generalization ability of RNN in dealing with the temporal data of nonlinear dynamic systems, Kumar et Al. [30], [31], [32], [33], [34]. have conducted extensive research based on RNN. However, this study focuses more on real-time guidance of trainers' EEG data rather than EEG classification or prediction. For this purpose, we adopt a personalized weighting scheme to capture temporal correlations in the data and utilize an adaptive threshold for constraining and guiding the data, thereby achieving the training objectives.

In this paper, we developed a complete neurofeedback system supporting an adaptive auto thresholding function that analyzes the training state of a subject and automatically calculates the optimum threshold. Moreover, the proposed system supports interoperability with a commercial game engine; thus, high-quality content can be made easily. These features distinguish the proposed system from existing systems and can make neurofeedback training more effective.

III. ADAPTIVE AUTO THRESHOLDING

A. ACQUISITION AND PROCESSING OF EEG SIGNALS

Fig. 1 illustrates the overview of the proposed system. The front part of the system includes a set of hardware for extracting and amplifying EEG signals. The operating software consists of two modules. The first one analyzes the amplified EEG signals and compares their amplitudes with the thresholds set by a therapist to generate success or failure feedback. The other automatically adjusts thresholds to improve the training effect. The training content works with the operating software to increase success feedback and decrease failure feedback.

High-precision EEG measurement techniques have been developed, and the accuracy and performance of EEG measurements have significantly improved over the years. This paper utilized NEURONFLEX [35], which follows the P2 communication protocol of the OpenEEG module and enables stable 2-channel EEG measurements over an extended period of time. It measures raw data between 0 and 1023 expressed in 10-bits at 256 times per second and transmits the data to the PC. The transmitted raw data were converted into a potential value in the range of -512 μV to $+511$ μV. The 256 converted data were divided into eight packets and transmitted to a digital signal processing (DSP) module. The DSP module performed the following tasks: first, a power spectrum analysis was performed on the real-time EEG signal via fast Fourier transform (FFT) [36]. The power spectrum analysis shows the amplitude of each frequency by converting the EEG signals in the time domain into the frequency domain. This paper applied FFT to 2048 sampling data measured for 8 s. The sampling rate of the raw data was 256 Hz; therefore, the amplitudes of the frequency ranging from 0 Hz to 128 Hz were obtained; Second, the DSP performed band-pass filtering of EEG signals in the training frequency range. Two types of digital filters are commonly used in discrete signal processing. Infinite impulse response (IIR) type filter has a regressive function that uses the previous output as the current input,

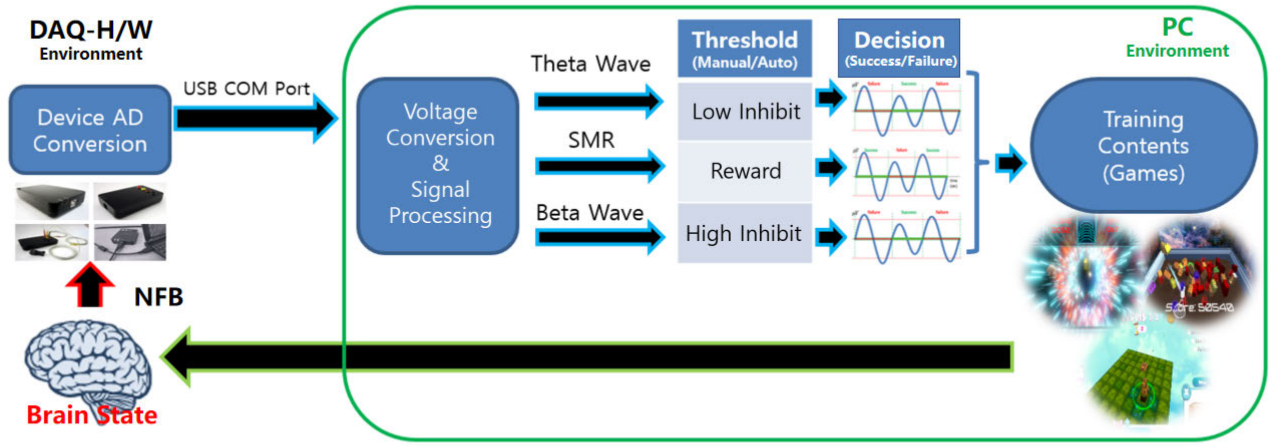

FIGURE 1. Overview of the neurofeedback training system: EEG data acquisition (red arrow), EEG signal transmission from the amplifier to the PC (blue arrow), visual conduction of the training content (green arrow).

TABLE 1. EEG frequency ranges and the types of brainwaves used in neurofeedback training.

Brainwave	EEG Frequency (Hz)	Type
Theta	4–7	Inhibit
SMR	12–15	Reward
High beta	22–36	Inhibit

requiring fewer orders for efficient filtering than the finite impulse response (FIR) filter. Thus, an IIR band-pass filter was used to extract brainwaves in the EEG frequency range, as shown in Table 1.

Equation (1) expresses the IIR-based band-pass filter used in the proposed system for extracting the SMR (12 to 15 Hz).

$$y[t] = b_0x[t] + b_1x[t-1] + b_2x[t-2] + a_0y[t-1] + a_1y[t-2], \tag{1}$$

where $x[t]$ and $y[t]$ are the input and output values at time t, and b_i and a_i are the coefficients of the feedforward and feedback filters of order 2 and 1, respectively. These coefficients were determined experimentally using the Iowa Hills filter design system [37] and an elliptical polynomial as follows:

$$b_0 = 0.3679,\ b_1 = -0.7063,\ b_2 = 0.3679$$
$$\text{and } a_0 = -1.8702,\ a_1 = 0.9706.$$

Fig. 2 shows the result of magnitude response generated by the filter in Equation (1). Intuitively, this filter amplifies the signals from 12 Hz to 15 Hz. Fig. 3 shows the real-time EEG signals (in black) and three band-pass filtered signals: theta waves (in red), SMR (in green), and high beta waves (in blue).

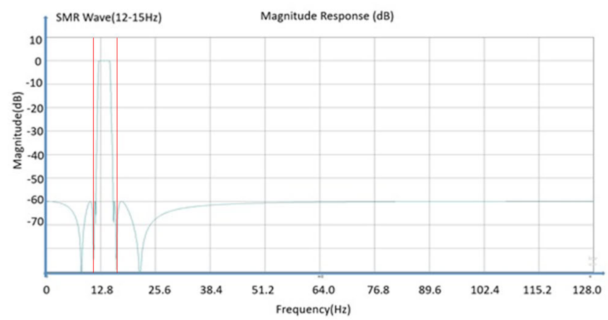

FIGURE 2. Magnitude response of the IIR filter in Equation (1).

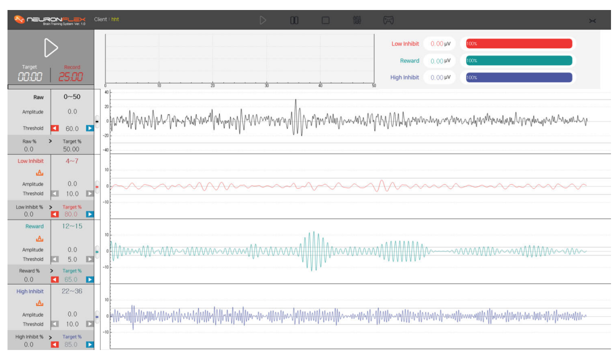

FIGURE 3. Real-time EEG signals and three band-pass filtered signals of theta wave (low inhibit), SMR (reward), and high beta wave (high inhibit).

B. DECISION OF SUCCESS AND FAILURE SECTION

The proposed neurofeedback system analyzed theta waves (4–7 Hz), SMR (12–15 Hz), and high beta waves (22–36 Hz) in EEG signals to provide feedback to the subjects. The theta and high beta waves are the inhibit frequencies; a failure feedback was generated when the amplitude of their frequencies exceeded the threshold set by the therapist. By contrast, the SMR corresponds to the reward frequency; a success feedback was generated when the amplitude of its frequency exceeded the threshold set by a therapist. The generated feedback was delivered as input to the training content, provided in the form of a video game, determining the game progress. Consequently, to proceed in the game as intended by the subject, the amplitudes of theta and high beta waves need to be maintained below

FIGURE 4. Decision of success and failure sections in theta wave (low inhibit), SMR (reward), and high beta wave (high inhibit).

the threshold values. In addition, the amplitude of the SMR should remain above the threshold. Through real-time feedback training, a subject learns to regulate one's brainwave conditions. This training mechanism was designed to set an optimum threshold that can help create precise feedback and improve the training effect. A comparison with a threshold was periodically made because EEG signals are oscillatory waves with period and amplitude. In the SMR corresponding to frequency domain of 12–15 Hz, a success feedback was generated when the sum of the power values (E) in the corresponding frequency domain was greater than or equal to the threshold, as shown in the following equation:

$$E = \sum_{k=12}^{15} |f_k| \geq \tau_{SMR}, \tag{2}$$

where f_k is the amplitude of frequency k, and τ_{SMR} is the threshold of SMR.

In a similar manner, a failure feedback was generated for theta and high beta waves, when the sum of the power values in the corresponding frequency domain was greater than or equal to the thresholds of theta and high beta waves. The system analyzed the power of the EEG frequency for the last 0.25 s every 0.125 s, so success or failure feedback is also generated every 0.125 s.

Fig. 4 shows the feedback generated by applying the proposed method to the theta wave (low inhibit), SMR (reward), and high beta wave (high inhibit). In the reward signal frequency, the sections marked in green lines are the periods in which the success feedback was generated. Similarly, in the inhibit signal frequencies, the sections marked in red lines are the periods in which the failure feedback was generated.

C. COMPUTING THRESHOLDS

A substantial amount of failure feedback was generated when a high threshold value of the reward frequency (SMR) was set for a subject who did not undergo neurofeedback training, making the training ineffective. By contrast, a success feedback was generated in most cases when a low threshold value of the reward frequency was set, making the content too easy for the subject. However, in this case, the subject did not achieve the desired training effect. This observation also holds true for the inhibit frequency. Therefore, a therapist needs to clearly identify the condition of a subject and carefully adjust the thresholds of the reward and inhibit frequencies to improve the effectiveness of training.

This paper used the auto thresholding method proposed by Shin et al. [38]. The proposed system allows a therapist to designate a desired target success rate for the reward and inhibit frequencies. The system analyzes the success ratio for a specific time for each training frequency and uses the ratio to automatically calculate a threshold that can ensure the desired success rate designated by the therapist. The success rate (%) S_t at current time t can be computed as follows:

$$S_t = \frac{N_S \times 0.125}{T} \times 100, \tag{3}$$

where T is a specific period during which the success rate is calculated (typically $T = 1$, 2, 4, or 8 s) and N_S is the total number of occurrences of success for period T. The constant 0.125 was multiplied because success and failure were determined every 0.125 s.

Suppose that a therapist designates the desired success rate $\widehat{S}$ for the reward frequency (SMR). The current success rate S_t can be equal to or greater than $\widehat{S}$ if $N_S = \lceil \widehat{S} \times \frac{T}{12.5} \rceil$, derived from Equation (3). From Equation (2), E is obtained every 0.125 s. The results can be arranged in descending order as follows:

$$E_1 \geq E_2 \geq \cdots \geq E_{N_S} \geq E_{N_S+1} \geq \cdots \tag{4}$$

In the reward frequency, the desired success rate $\widehat{S}$ can be achieved by setting the threshold τ_{SMR} between the E_{N_s} and E_{N_s+1}. By contrast, in the inhibit frequency, the above results need to be arranged in ascending order. Moreover, a new threshold should be selected between the E_{N_s} and E_{N_s+1} to obtain a designated success rate.

Thus, the calculated thresholds are effective under the assumption that brainwaves occurring for the previous T are repeated for the next T. However, this assumption does not typically hold true in real training. Consequently, the thresholds obtained in the above method do not guarantee the desired success rate. To solve this problem and acquire an optimum threshold close to the desired success rate, it is necessary to consider all patterns of brainwave data of the previous m intervals. This study proposes a method for obtaining an optimum threshold by considering all previous eight intervals ($m = 8$). Let $S_{t-kT}(\tau)$ be the success rate determined by threshold τ at the k-th previous interval. The cumulative cost function $C(\tau)$ of the difference between the desired success rate $\widehat{S}$ and each success rate for the eight intervals can be defined as follows:

$$C(\tau) = \sum_{k=1}^{8} w_k \left|\widehat{S} - S_{t-kT}(\tau)\right|^2, \tag{5}$$

where w_k is the weight of $S_{t-kT}(\tau)$ and satisfies $\sum w_k = 1$. Because the brainwave of the subject was most likely to

Algorithm 1 The Pseudo-Code of the Proposed System

```
Procedure: EEG Acquision & Processing
while All_System_Running do
    eeg_data ← acquire_eeg();                              // EEG acquisition
    preprocessed_d ← preprocess_eeg(eeg_data);             // EEG preprocessing
    USB_transmit_data(preprocessed_d);                     // EEG transmission
Procedure: Auto Thresholding
while Control_System_Running do
    converted_d ← conv_vol(preprocessed_d);                // Voltage conversion
    processed_d ← process_eeg(converted_d);                // EEG IIR filtering
    threshold ← calculate_threshold(processed_d);          // Adaptive threshold calculation
    decision ← Gen_decision(processed_d, threshold);       // Decision generation (Success/Failure)
    UDP_transmit_decision(decision);                       // Decision transmission using UDP
    TCP_transmit_ui_control(ui_control);                   // UI control transmission using TCP
Procedure: Running Training Contents
while Game_Contents_Running do
    packets ← receive_packets();                           // Receive packets
    update_data(packets);                                  // Update EEG amplitude data and decision
                                                              data
    if decision == "Success" then
        generate_reward_content();                         // Positive control of training content
    else
        generate_inhibit_content();                        // Negative control of training content
    TCP_transmit_ui_control(ui_control);                   // Game UI control transmission using TCP
```

repeat the latest pattern, the following weights were used:

$$w_1 = \frac{128}{255},\ w_2 = \frac{64}{255},\ w_3 = \frac{32}{255},\ w_4 = \frac{16}{255},$$
$$w_5 = \frac{8}{255},\ w_6 = \frac{4}{255},\ w_7 = \frac{2}{255},\ w_8 = \frac{1}{255}. \tag{6}$$

These weights can be obtained by $w_k = \frac{2^{8-k}}{2^8-1}$. The threshold obtained from Equation (4) was set as the initial value τ_0 to minimize $C(\tau)$ of Equation (5). Numerical optimization [39] can be performed to calculate an optimal τ^*. The optimal threshold was not calculated at every moment. However, the threshold was automatically calculated when the difference between the present success rate S_t and the target $\widehat{S}$ exceeded a specified allowable error (ε_S) for specified time (ε_T). Fig. 5 shows an example of these control parameters, where $\widehat{S}$, ε_S, and ε_T were set to 65%, 5%, and 4 s, respectively. The thresholds were automatically updated when the success rate of the reward frequency was below 60% (or above 70%) for over 4 s. Consequently, the adaptive auto thresholding function can help a therapist with neurofeedback training and improve the training efficiency. The main procedures of adaptive auto thresholding algorithm are described in Algorithm 1.

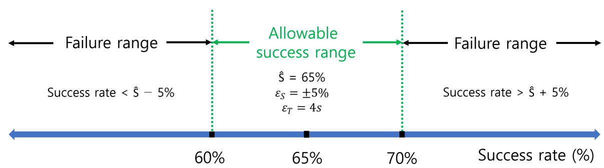

FIGURE 5. Example of control parameters and allowable success range: target success rate ($\hat{S}$ = 65%), allowable error (ϵ_S = 5%) and time (ϵ_T = 4 s).

D. RESULT OF AUTO THRESHOLDING

The proposed auto thresholding algorithm was implemented in C++ language and executed on a PC integrating an Intel i7-4790 3.6 GHz CPU, 16 GB main memory, and an NVIDIA GeForce GTX770 graphic card. Raw brainwave data were measured for 10 min to evaluate the performance of the proposed method. An IIR-based band-pass filter was applied to the raw data, and brainwave data of the SMR domain were extracted. An initial threshold $\tau = 3.5\ \mu V$ and S of 65% were set for the SMR obtained. The success or failure feedback was generated at 0.125 s intervals to calculate the average success rate. Table 2 shows the various experimental results; the last column shows the average success rate of each experiment. The average success rate of the first experiment was calculated without applying the auto thresholding function. An average success rate of 73.5% was obtained. Therefore, the initial threshold was set to a low value, and success feedback was generated in most cases. In this case, the threshold value should be adjusted to a high value to achieve the target success rate of 65%.

In the second experiment, for the same target success rate and initial threshold, the auto thresholding method was

TABLE 2. Auto thresholding experiments for SMR with different allowable errors and allowable times.

Experiment No.	1	2	3	4	5	6	7	8
Target Success Rate (%)	65	65	65	65	65	65	65	65
Allowable Error (%)	-	10	5	3	1	5	5	5
Allowable Time (s)	-	1	1	1	1	2	4	6
Number of Threshold Renewals	-	98	177	260	320	86	45	33
Average Success Rate (%)	73.5	69.2	66.9	66.3	65.1	67.1	68.1	85.5

activated with an $\varepsilon_s = 10\%$ and $\varepsilon_T = 1$ s. For the SMR data for 10 min, 98 new thresholds were automatically calculated; an average success rate of 69.2% was obtained. The same conditions were applied from the third to the fifth experiments. The allowable error gradually decreased. The thresholds were renewed more frequently as the allowable error decreased, resulting in a success rate closer to the target success rate.

The same allowable error was applied from the sixth to eighth experiments, but the allowable times were different. The number of renewals of the threshold and average success rate were measured. The thresholds were renewed less frequently as the allowable time increased. Thus, the average success rate was far from the target success rate. When the allowable time was 6 s, the average success rate was beyond the allowable error range of the target success rate.

Table 3 shows different types of experiments where a therapist changes the target success rate, allowable error, and time every 1 min. The raw data of brainwaves were measured for 9 min. As demonstrated by the experimental results, the proposed auto thresholding technique calculated an optimal threshold that can produce a success rate closest to the target success rate. Fig. 6 shows the target success rates and actual success rates of the experiment in Table 3. Exact success or failure feedback can improve the training effect. If a fixed threshold is used, the subjects obtains significantly high or low success rates, which can not produce good training results in general. The proposed auto thresholding technique can effectively solve this problem and improve the training effect.

Our automatic threshold adjustment method does not significantly increase the computational cost compared to existing systems that manually adjust thresholds. Further calculations include only the numerical optimization of Equation (5). Moreover, this calculation can also be controlled by therapist-specified control parameters such as allowable error(ε_S) and time(ε_T). Other processing steps are also included in most existing systems, so this is not a critical issue for performance comparison.

IV. PRODUCTION OF TRAINING CONTENTS

A. INTEROPERABILITY WITH A COMMERCIAL GAME ENGINE

The conventional training content is primarily created by the SDK provided by EEG devices and the operating system.

TABLE 3. Auto thresholding experiments for various target success rates changing in real time.

Time (min)	1	2	3	4	5	6	7	8	9
Target Success Rate (%)	40	45	50	55	60	65	70	80	90
Allowable Error (%)	7	5	3	7	5	3	7	5	3
Allowable Time (s)	4	4	4	2	2	2	1	1	1
Average Success Rate (%)	43	44	47	54	57	62	69	80	88

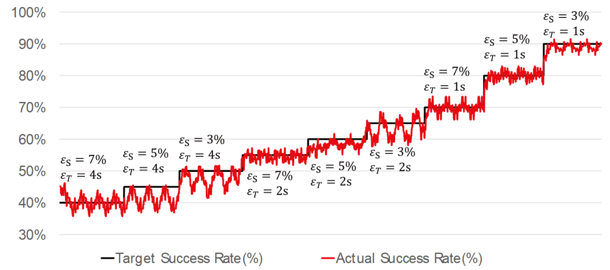

FIGURE 6. Auto thresholding results for various target success rates changing in real time and actual success rates.

Thus, creating new content is a highly laborious and time-consuming task. To create high-quality training content conveniently and quickly, the proposed system supports interoperability with unity3D [40], a widely used commercial game engine. Eight types of outputs are available depending on the combination of success or failure feedback for theta, SMR, and high beta waves. The proposed system uses an inter-process communication (IPC) module and transmits the outputs to the training content every 0.125 s through a user datagram protocol (UDP). Figure 7 shows the IPC module between the EEG control system and game engine. We utilized C++ language to encapsulate the required IPC data into static library functions using object-oriented programming and these functions were invoked by the unity3D engine to achieve real-time data transmission.

Thanks to the IPC module, existing games available in the online asset store can be reused and customized as educational content with expert guidance from the training center's clinical experts. For pilot testing, we customized content scenarios, including game character selection, overall color tone (leaning toward the dark side), specified audio effect frequencies (alternating between high and low frequencies), and other elements. We also employed artificial intelligence (AI) characters to ensure automatic game progression, and used decision data transmitted through IPC to control the game, including visuals, character movement speed, sound effects, game progression, and other controls. As a result, this interoperability between systems and game engines allows developers to use the full capabilities of the unity3D engine and significantly reduces the time and cost required to create training content.

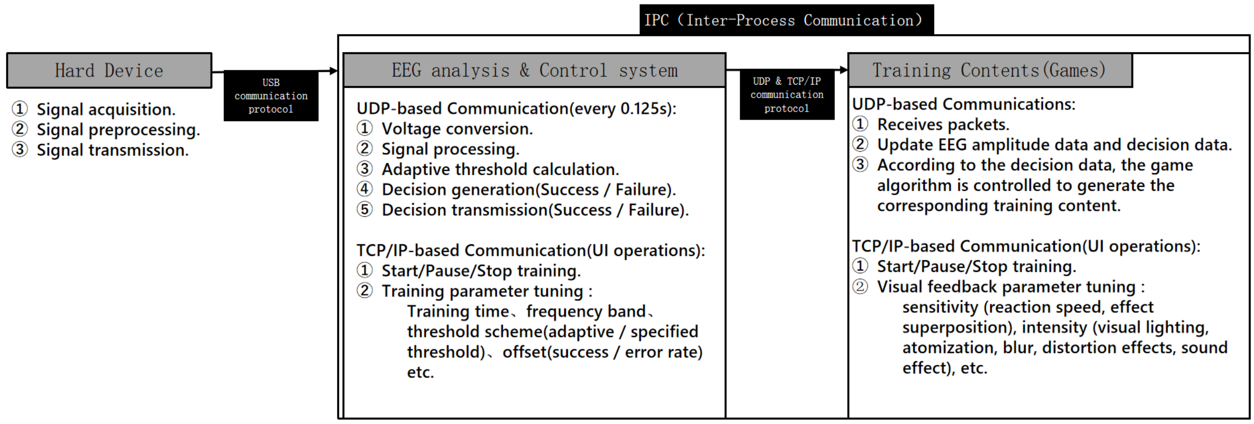

FIGURE 7. The inter-process communication (IPC) module of proposed system.

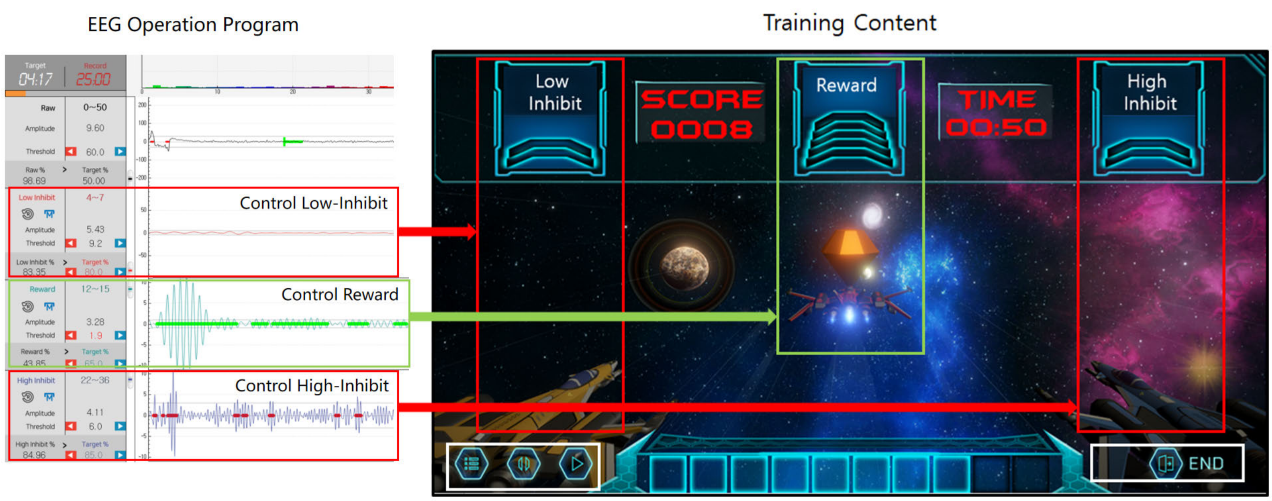

FIGURE 8. Failure feedback (theta), success feedback (SMR), and failure feedback (high beta) transmitted to a training content through the IPC module.

Fig. 8 shows an example of aircraft racing content controlled by the real-time outputs transferred by the IPC module. For example, the success feedback of the reward frequency (SMR) increases the speed of a player character (PC) aircraft. However, the failure feedback of the low (theta) or high (high beta) inhibit frequency increases the speeds of the non-player character (NPC) aircrafts on the left and right sides or darkens the background image of the training content. Success feedback during training leads to the game progress, whereas, failure feedback hinders it; thus, subjects are induced to increase success feedback, training them to control their brainwaves (see Supplementary Video).

B. NEUROFEEDBACK AND CONTROL OF TRAINING CONTENTS

Fig. 9 shows more examples of training contents produced using the proposed system and unity3D engine. Table 4 lists the training contents and their mappings between feedback and controlling the content. The control protocols for each training content were carefully determined by EEG clinical experts to maximize the training effect.

FIGURE 9. Various training contents for neurofeedback training: (a) Inner Tube, (b) Car Racing, (c) Brick Breaker, and (d) Fox Racing.

TABLE 4. Neurofeedback and control of training contents.

Content Title	Brainwave	Type	Feedback	Control of Content
Inner Tube	Theta	Low Inhibit	Success	The plane flies at normal speed.
			Failure	The image becomes dark.
	SMR	Reward	Success	The plane flies faster.
			Failure	The plane stops.
	High beta	High Inhibit	Success	The plane flies at normal speed.
			Failure	The sound is reduced.
Car Racing	Theta	Low Inhibit	Success	The car moves at normal speed.
			Failure	The image becomes blurry.
	SMR	Reward	Success	The car moves faster.
			Failure	The car stops.
	High beta	High Inhibit	Success	The car moves at normal speed.
			Failure	The image becomes blurry.
Brick Breaker	Theta	Low Inhibit	Success	The ball moves at normal speed.
			Failure	Red unbreakable blocks are created.
	SMR	Reward	Success	The ball moves at normal speed.
			Failure	The ball moves slowly.
	High beta	High Inhibit	Success	The ball moves at normal speed.
			Failure	Blue unbreakable blocks are created.
Fox Racing	Theta	Low Inhibit	Success	The fox moves at normal speed.
			Failure	The image becomes dark.
	SMR	Reward	Success	The fox blows fire in its tail and moves faster.
			Failure	The fox moves at normal speed.
	High beta	High Inhibit	Success	The fox moves at normal speed.
			Failure	The gift boxes turn into pumpkins and the score decreases.

TABLE 5. ID, age, CAT results, and inspection dates of the subjects.

ID	Age	CAT Results	First Inspection Date	Last Inspection Date
S1	5	Reduced attention in the sustained attention test to response task	20 April 2021	2 August 2021
S2	9	Reduced attention in the Flanker test, reduced attention in the spatial working memory test	27 November 2021	28 March 2022
S3	11	Boundary attention in the visual selective attention test, boundary attention in the sustained attention test to response task, reduced attention in the Flanker test, reduced attention in the spatial working memory test	13 November 2021	30 May 2022
S4	6	Reduced attention in the visual selective attention test, boundary attention in the auditory selective attention test, reduced attention in the sustained attention test to response task, reduced attention in the Flanker test	2 September 2021	30 November 2021
S5	8	Reduced attention in the visual selective attention test, reduced attention in the auditory selective attention test, reduced attention in the sustained attention test to response task, reduced attention in the Flanker test	30 March 2021	20 May 2022

V. PILOT TEST

A neurofeedback training was conducted on children with ADHD symptoms using the proposed training system. This experiment aimed to conduct a pilot study to confirm the usability of the developed training system.

A. SUBJECTS AND EXPERIMENTAL PROTOCOL

According to the results of the Comprehensive Attention Test (CAT) [41], five children with a potential for ADHD were targeted. The subjects were classified as 'reduced' and 'boundary' rather than 'normal' in several attention tests to determine the possibility of ADHD. A neurofeedback training system was used to evaluate whether these test items were improved. Table 5 shows the subject ID and age, CAT results, and EEG and CAT inspection dates before and after training.

Neurofeedback training was conducted at an institute [42] in Seoul, Korea. The subjects were trained twice a week for 25–30 min per session. The training was conducted using only serious video games developed by this system. No other training was conducted in parallel and no psychiatric drugs were used during the training period. After training for approximately 20 times, the brainwave signals before and after training were compared; Section V-B describes the results. CAT results before and after training were also compared; Section V-C describes these results.

B. BRAIN MAPPING RESULTS

The training results were analyzed based on the brainwave frequency power. The brainwave frequency power was measured by attaching an EEG sensor based on a 10–20 system [43]. In this study, the measuring instruments were attached to F3, F4, T3, T4, C3, C4, Cz, and Oz. F3 and F4 are symmetrical positions of the frontal lobes, T3 and T4 are symmetrical positions of the temporal lobes, and C3 and C4 are symmetrical positions of the central lobes. EEG was also measured at Cz and Oz in the parietal and occipital lobes (Fig. 10).

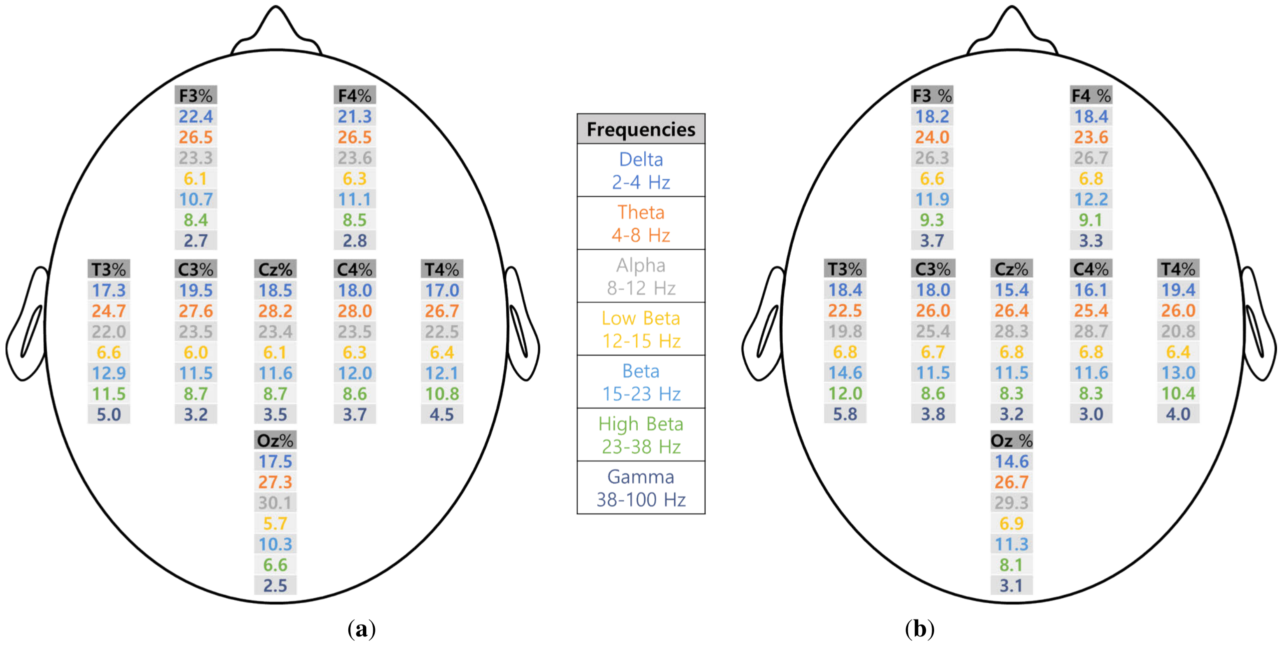

FIGURE 10. Brainwave relative map of S1: (a) before and (b) after neurofeedback training.

TABLE 6. CAT result of S3 before and after neurofeedback training.

		Visual Selective Attention Test (Before/After)	Auditory Selective Attention Test (Before/After)	Sustained Attention Test to Response Task (Before/After)	Flanker Test* (Before/After)	Divided Attention Test* (Before/After)	Spatial Working Memory Test* (Forward) (Before/After)	Spatial Working Memory Test* (Backward) (Before/After)
S3 (Before / After) : (13 Nov 2021 / 30 May 2022)	Omission error	normal / normal	normal / normal	normal / normal	normal / normal	normal / normal	-	-
	Commission error	normal / normal	normal / normal	normal / normal	normal / normal	normal / normal	-	-
	Response time	boundary/normal	normal / normal	boundary/normal	reduced/ reduced	normal / normal	-	-
	Response time(SD**)	normal / normal	normal / normal	normal / normal	reduced/normal	normal / normal	-	-
	Correct response	-	-	-	-	-	reduced/reduced	reduced/reduced
	Memory span	-	-	-	-	-	boundary/boundary	reduced/reduced

* Depending on the age of the subjects, the Flanker test, divided attention test, and spatial working memory test were not performed in the CAT.**Standard deviation.

Brainwaves are classified into delta, theta, alpha, low beta, beta, high beta, and gamma waves according to the frequency band. The brainwave relative map shows the relative intensity of the amplitude of each brainwave frequency as a percentage with respect to the sum of all amplitudes of the brainwave frequencies. Fig. 10a and b show the relative maps of subject S1 before and after neurofeedback training, respectively. Taking the F3 position as an example, the percentages of theta and low beta brainwaves before and after training were 26.5% and 6.1% and 24.0% and 6.6%, respectively; therefore, the inhibit frequency power decreased, and the reward frequency power increased.

Fig. 11 shows the brainwave relative color maps of the brainwave relative map of subject S1. Relative color maps were generated separately by dividing the 2–4 Hz frequency range. The percentage values of frequencies calculated at the eight measurement locations were converted to color, and smooth-varying color areas were created for the entire brain area.

The 2–4 Hz brainwave, which was strongly measured in the frontal lobe of the subject, weakened after neurofeedback training. The 4–6 Hz brainwave also weakened after training. The strong low-frequency (2–8 Hz) brainwave in the frontal lobe indicates that the brain's arousal control function is weak, commonly observed in children with ADHD. After the neurofeedback training developed in this study, the amplitudes of low-frequency brainwaves in the frontal lobe weakened.

The frontal theta-beta ratio (TBR) also decreased. The TBR is the ratio between theta and beta frequency powers;

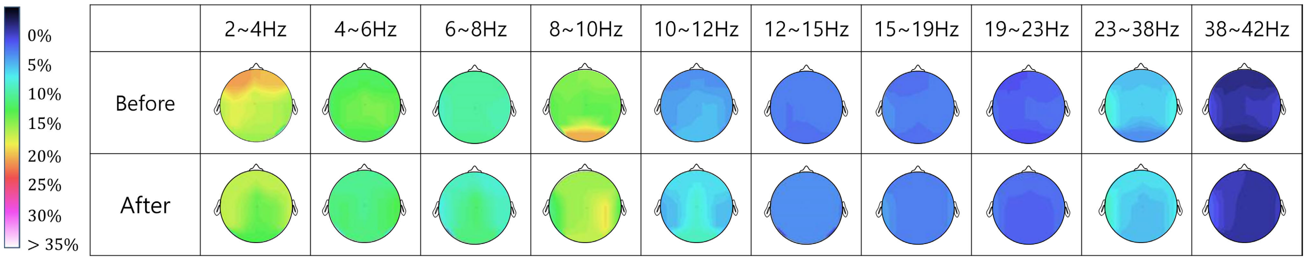

FIGURE 11. Brainwave relative color maps of S1 before and after neurofeedback training.

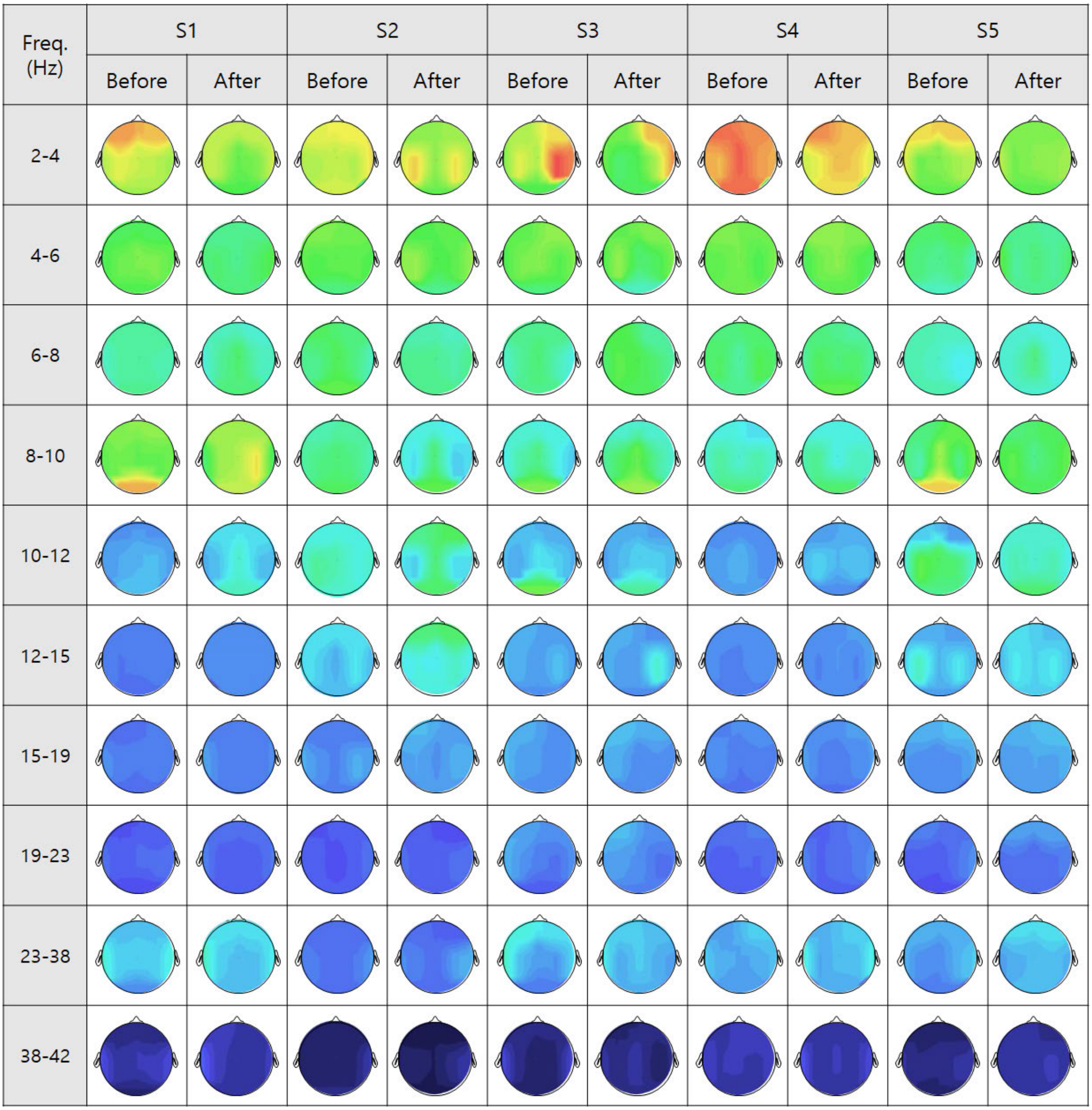

FIGURE 12. Brainwave relative color maps of all subjects before and after training.

TABLE 7. CAT result of all subjects before and after neurofeedback training.

		Visual Selective Attention Test (Before/After)	Auditory Selective Attention Test (Before/After)	Sustained Attention Test to Response Task (Before/After)	Flanker Test* (Before/After)	Divided Attention Test* (Before/After)	Spatial Working Memory Test* (Forward) (Before/After)	Spatial Working Memory Test* (Backward) (Before/After)
S1 (Before / After) : (20 Apr 2021 / 2 Aug 2021)	Omission error	normal / normal	normal / normal	normal / normal	-	-	-	-
	Commission error	normal / normal	normal / normal	reduced/boundary	-	-	-	-
	Response time	normal / normal	normal / normal	normal / normal	-	-	-	-
	Response time(SD**)	normal / normal	normal / normal	normal / normal	-	-	-	-
S2 (Before / After) : (13 Nov 2021 / 30 May 2022)	Omission error	normal / normal	normal / normal	normal / normal	reduced/normal	normal/normal	-	-
	Commission error	normal / normal	normal / normal	normal / normal	normal / normal	normal / normal	-	-
	Response time	normal / normal	normal / normal	normal / normal	normal / normal	normal / normal	-	-
	Response time(SD)	normal / normal	normal / normal	normal / normal	normal / normal	normal / normal	-	-
	Correct response	-	-	-	-	-	reduced/ reduced	reduced/normal
	Memory span	-	-	-	-	-	reduced/normal	reduced/normal
S3 (Before / After) : (13 Nov 2021 / 30 May 2022)	Omission error	normal / normal	normal / normal	normal / normal	normal / normal	normal / normal	-	-
	Commission error	normal / normal	normal / normal	normal / normal	normal / normal	normal / normal	-	-
	Response time	boundary/normal	normal / normal	boundary/normal	reduced/ reduced	normal / normal	-	-
	Response time(SD**)	normal / normal	normal / normal	normal / normal	reduced/normal	normal / normal	-	-
	Correct response	-	-	-	-	-	reduced/reduced	reduced/reduced
	Memory span	-	-	-	-	-	boundary/boundary	reduced/reduced
S4 (Before / After) : (2 Sep 2021 / 30 Nov 2021)	Omission error	normal / normal	normal / normal	normal / normal	normal / normal	-	-	-
	Commission error	normal / normal	normal / normal	normal / normal	normal / normal	-	-	-
	Response time	reduced/reduced	boundary/normal	reduced/ reduced	reduced/reduced	-	-	-
	Response time(SD)	normal / normal	normal / normal	normal / normal	reduced/normal	-	-	-
S5 (Before / After) : (30 Mar 2021 / 20 May 2022)	Omission error	normal / normal	normal / normal	normal / normal	reduced/normal	-	-	-
	Commission error	normal / normal	normal / normal	normal / normal	normal / normal	-	-	-
	Response time	reduced/normal	reduced/normal	reduced/normal	reduced/boundary	-	-	-
	Response time(SD)	normal/boundary	normal / normal	boundary/normal	reduced/boundary	-	-	-

* Depending on the age of the subjects, the Flanker test, divided attention test, and spatial working memory test were not performed in the CAT.**Standard deviation.

frontal TBR reduces as attentional control improves [44]. The percentages of the theta and low beta wave powers in the frontal left area of the brain (F3) before and after training were 26.5% and 6.1% and 24.0% and 6.6%, respectively. This indicates a decrease in the TBR (Fig. 10).

C. CAT RESULTS

This subsection evaluates the effectiveness of the training from a medical perspective. The CAT results before and after training in the five subjects were compared. Table 6 shows the CAT results for subject S3.

The visual selective attention evaluated according to the average response time before and after training, was 'boundary' and 'normal,' respectively. The sustained attention to response task evaluated according to the average response time before and after training was 'boundary' and 'normal,' respectively. The attention in the Flanker test evaluated according to the standard deviation of the response time before and after training, was 'decreased' and 'normal,' respectively. All five subjects showed improved CAT results after neurofeedback training, and no parameters worsened.

VI. CONCLUSION

This study aimed to develop a sophisticated neurofeedback system for effective training. The proposed system includes an adaptive thresholding function that automatically adjusts the thresholds according to the target success rates, allowable error, and time set by therapists. This system creates accurate feedback at 0.125 s intervals by comparing the thresholds with the power spectrum values. In addition, the generated success or failure feedback is analyzed to calculate the success rate for a particular duration. In case where the calculated success rate exceeds the error range of the target success rate set by the therapist, the system analyzes the previous brainwave patterns of the subject and automatically calculates an optimized threshold that can lead to the target success rate. Moreover, the proposed system is compatible with existing game engines, such as unity3D, resulting in the rapid production of various training contents.

A pilot test on five children with ADHD symptoms was performed to demonstrate the effectiveness of the proposed system and training contents. After training for 3–4 months, all subjects showed significant improvements in the brainwaves and CAT results.

The proposed method can improve neurofeedback training effects and the limitations of conventional face-to-face training can be resolved. Adjusting the thresholds is usually done by an experienced therapist, and employment and expenses are charged accordingly. When using the auto thresholding method proposed in this study, training can be performed without a therapist, or one therapist can manage multiple EEG training at the same time, thereby reducing the constraints of employment, cost, and time.

The developed system supports high scalability. Neurofeedback training can be started immediately for any EEG other than SMR, theta, and high beta, which were the training targets in our study, just by setting the frequency band, EEG type (reward or inhibit), initial threshold, and target success rate. The developed system is also compatible to other EEG devices. Most EEG devices adopt a sampling rate of 256 or 512 Hz, and if the EEG device manufacturer provides a protocol to obtain sampled EEG data, it can be used in the developed system. Training contents are also made with a widely used commercial game engine, so it is easy to change training contents or add new contents.

The developed neurofeedback system has been implemented and utilized in the brain training center where the pilot test was conducted.

Furthermore, a human factor study will be conducted to analyze the outcomes before and after training to prove the practicability of the proposed system.

APPENDIX
EXPERIMENTAL RESULTS OF ALL SUBJECTS BEFORE AND AFTER TRAINING

In this appendix, we present experimental results of all subjects before and after training.

A. BRAINWAVE RELATIVE COLOR MAPS OF ALL SUBJECTS BEFORE AND AFTER TRAINING

The brainwave relative color maps of all five subjects are presented in the Fig. 12.

B. CAT RESULTS OF ALL SUBJECTS BEFORE AND AFTER TRAINING

The CAT results for all the subjects are presented in the Table 7.

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