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Development of virtual key control system through Fuzzy-based EEG analysis and activation in BCI environment

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Abstract: Electroencephalography (EEG) is a non-invasive technique that measures the brain's electrical activity via electrodes placed on the scalp. This technology is widely utilized in health care, neurofeedback, emotional ICT, and neuromarketing. A critical aspect of EEG-based Brain-Computer Interface (BCI) systems is the extraction of stable and high-level brain signal features. This paper presents a study employing fuzzy logic in a BCI environment to measure, classify, and quantify EEG signals. Based on this approach, a system was developed that analyzes and activates EEG signals to control devices through virtual key input. The proposed system enables EEG-based user interaction with mobile devices via a virtual keypad. The results suggest that BCI control services can be expanded to various industrial applications through continuous development and service enhancement.

Keywords: Brain computer interface; Mobile control; Electroencephalogram; Fuzzy; Human computer interface.

1. Introduction

Electroencephalography (EEG) measures the brain's electrical activity using electrodes placed on the scalp, providing non-invasive insight into neural processes. EEG signal processing has found applications in medical diagnostics, neurofeedback, emotion-aware computing, and neuromarketing. A BCI (Brain-Computer Interface) refers to technology that enables individuals to control external systems using brain activity alone, bypassing traditional neuromuscular pathways[1][2].

BCI (Brain-Computer Interface) refers to a technology that allows a user to communicate with an external device such as a computer system without interference from biological tissues such as peripheral nerves and muscles. BCIs can be applied to various applications for people with movement disorders to interact with their surroundings[3-5]. BCI-based motor imagery refers to the mental task of simply imagining the movement without moving the body, such as the right or left hand. Recently, research on moving a robot arm or controlling a wheelchair through motor association is being conducted for healthy people as well as people with disabilities. An electroencephalogram (EEG) is a recording of brain potential obtained by attaching electrodes to the human scalp. It is well known to measure EEG signals in a non-invasive way. For EEG measurement, an EEG cap in the form of a hat that follows the 10-10 system or 10-20 system, which has been internationally standardized by dividing the skull in a certain ratio, is used. Electrodes for EEG measurement such as Ag/AgCl can be attached to the EEG

Cap[6]. These electrodes, placed on the scalp, can measure EEG signals that reflect post-synaptic potentials of pyramidal cell populations, which are mainly present in the cerebral cortex[7].

EEG is widely used in brain cognitive function research due to its advantages of being relatively inexpensive, easy to carry, and easy to use compared to other EEG measuring devices. It has high temporal resolution, so it can analyze electrical changes occurring in the brain in real time in units of 1/1000 of a second. EEG's high temporal resolution allows researchers to analyze EEG signals in multiple domains. It can be used as a suitable tool for studying brain cognitive function as it can distinguish and analyze bottom-up and top-down mechanisms that are reflected in the brain's cognitive processing process. On the other hand, EEG basically has a low spatial resolution due to insufficient conductivity of the skull, and thus has limitations in identifying the source of EEG components involved in cognitive processing[8][9]. Therefore, recently, in order to overcome the low spatial resolution of EEG, fMRI (functional magnetic resonance imaging), which has high spatial resolution, and EEG are combined to complement each other. There is an increasing trend of research to accurately estimate the source of EEG signals involved in cognitive processing through the EEG source reconstruction algorithm[10].

Modern BCI systems focus on real-time interpretation of neural signals to facilitate interaction with external devices. Beyond assistive applications, BCI is increasingly used to enhance cognitive functions through neural modulation [11][12]. A typical BCI system consists of five stages:

- 1) Brain signal data collection step
- 2) Signal processing step
- 3) Feature extraction step
- 4) Classification stage
- 5) Feedback stage

Among these processing steps, the signal processing step, the feature extraction step, and the classification step have been manually performed by experts with considerable expertise.

An expert's erroneous judgment in the signal processing stage makes accurate EEG analysis difficult. Although much progress has been made in the field of BCI, BCI performance is still not greatly improved. The main factors are, first of all, that the EEG signal is not clear. Another factor is that the variation of signals between users is too diverse. These factors mean that stable and high-level brain signal feature extraction must be performed when implementing an EEG-based BCI system. As BCI technologies evolve, the demand for these technologies will continue to increase[13].

Deep learning, particularly Convolutional Neural Networks (CNN), has shown promise in improving feature extraction and classification in image recognition and

speech processing. These techniques have potential for application in EEG-based BCI systems [14][15].

Therefore, in this paper, we designed a platform that measures, classifies, and quantifies brain signals in a BCI environment based on basic research on BCI-based control services. In addition, reliability was secured by applying a fuzzy technique to minimize EEG measurement errors. Using this approach, a BCI-based mobile device control system was developed and signal connection between devices was implemented through virtual key control. Finally, a system was implemented a BCI-based virtual key control and mobile monitoring system that combines an EEG-based virtual keyboard and an EEG monitoring app.

2. Related works

2.1 Electroencephalogram (EEG)

EEG (Electroencephalogram) is an electrical signal that non-invasively measures the electrical activity of the brain by electrodes attached to the surface of the head. In 1875, British physiologist R. Caton first recorded weak electrical activity in the cerebral cortex of rabbits and monkeys using a galvanometer. This is known as the first report of EEG [16]. The EEG signal can be viewed spectrally using frequency analysis. In addition, EEG shows waveforms that vibrate in very complex and diverse patterns. Visual observation of the EEG waveform as it is not useful. Therefore, when observing and appropriately applying EEG, classification and analysis must be accompanied. In the case of EEG signals, Fourier transform and power spectrum analysis, which are classified according to frequency, are often used. The Fourier transform can be said to be a combination of simple oscillations in which EEG signals oscillate at specific frequencies. This is decomposed into each frequency component of the signal and the magnitude is displayed[17].

Figure 1 shows that spectrum analysis was performed using actual EEG signals and Fourier transform was performed based on it. In general, EEG signals are artificially delta- δ waves (0.2 to 3.99 Hz), theta- θ waves (4 to 7.99 Hz), alpha- α waves (8 to 12.99 Hz), and beta- β waves according to the range of vibrating frequencies. (13 ~ 29.99 Hz) and gamma- γ waves (30 ~ 50 Hz).

Delta waves are known as EEG signals mainly detected during deep sleep of normal people. Since artifacts generated by body or eye movements during EEG measurement may be reflected in EEG measurement data in the form of delta waves, care must be taken not to confuse noise and EEG when analyzing delta waves. Theta waves are known to be related to various cognitive functions such as working memory. It is known that alpha waves are mainly observed in a relaxed state. A phenomenon in which alpha waves are suppressed when one concentrates on a certain stimulus or requires mental effort is called alpha blocking. Alpha waves are also known to increase significantly when you do inner concentration. It is known to play an important role in perception and attention. In addition, when performing a cognitive task, an increase in alpha waves in cortical areas not related to the task is sometimes observed. Beta waves appear predominantly in a state of anxiety or

tension. It is known to be related to the sensorimotor cortex and is widely used in BCI research. Gamma waves are related to various cognitive functions, and are thought to be related to higher-order cognitive functions. Since gamma waves deal with the high-frequency components of the signal, careful attention must be paid to not to confuse the noise components of the EEG signal with EEG signals during analysis[18][19].

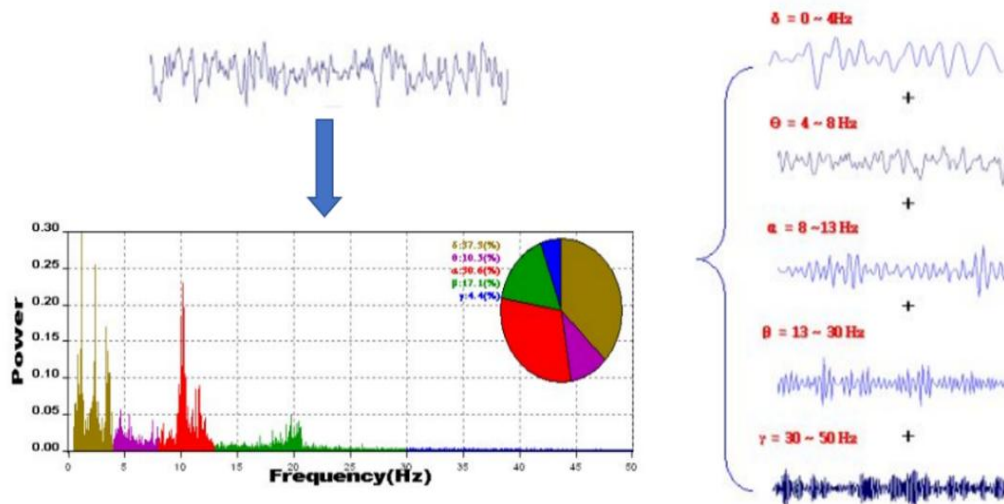


Figure 1. Fourier transform and spectrum analysis using real EEG signals

When analyzing EEG characteristics in a specific state, spectrum analysis and judgment must be performed. That is, the power spectrum distribution indicating the power distribution for each frequency component of 0 to 50 Hz must be observed as a whole. Then, the brain state is determined through changes in brain signal components. This power spectrum distribution shows slightly different aspects depending on the measurement area and range of the head surface. The cerebral cortex below the surface of the head is largely divided into the frontal lobe, parietal lobe, temporal lobe, and occipital lobe, and each area plays a slightly different role[20]. The occipital lobe corresponds to the occipital lobe. There is a primary visual cortex in N, which is responsible for primary visual information processing, and a parietal lobe near the parietal lobe has a somatosensory cortex in charge of motor/sensory-related information processing.

The BCI technology method can be divided into invasive and non-invasive types according to the region where the EEG signals are measured. In addition, it is divided into an EEG induction type and an EEG recognition type according to the characteristics of the EEG used[21]. Table 1 shows the methods and characteristics according to the classification criteria according to the EEG measurement region and the characteristics of the EEG used.

Table 1. Classification according to EEG measurement area and characteristics

Classification criteria	Method	Characteristic	Example
EEG measurement area	Invasive method	- Microchip implanted on the scalp to measure brain waves - Accurate measurement is possible, but surgery is required and there may be surgical side effects	- An experiment in which a mechanical arm was moved using the nerve signals detected in the brain by applying an EEG measuring microchip to the brain of a monkey (Duke University)
	Non-invasive method	- EEG measurement with helmet or headset type equipment - It is simple, but it is inevitable that noise is mixed - Difficult to measure accurately	- A method used in experiments of university research institutes or commercial products - NeuroSky's headset-type EEG measuring machine
EEG characteristics	EEG induction method	- How to induce and apply the appearance of specific brain waves - Since the actual intention of the user and the appearance of brain waves do not match, training is required to create specific brain waves.	- Electric appliance on/off experiment using brain waves - Distinction between positive and negative intentions
	EEG recognition method	- Recognize simple intentions/movements by analyzing brain waves - communicates the user's intentions to a computer or machine	- Analyzing brain waves to discriminate the user's arousal level - Cursor control for the disabled, text word selection control

The invasive method is capable of relatively accurate EEG measurement. However, it is expected that general use will be impossible because the burden on the user, such as surgical procedures and side effects, is very high. The non-invasive type has the advantage of being harmless to the human body and being simple, but has the disadvantage of being mixed with noise and difficult to accurately analyze EEG. Due to these advantages and disadvantages and characteristics, this paper used a non-invasive method using a headset.

2.2 EEG analysis method

2.2.1 Time base analysis method

A method of analyzing EEG on a time axis is the most commonly used analysis method in EEG analysis. It is a method of analyzing potentials measured in the brain over time. Analysis methods using ERP components are mainly used for time axis analysis. These ERP components are known to reflect different brain and cognitive functions. Studies that analyze an ERP component called P300, which is a positive peak value appearing at about 300 ms after sensory stimulation in the process of cognitive processing, are common. Figure 2 shows the derivation of the P300 component of the EEG[22]. In general, in P300 research, when the same stimulus is repeatedly applied, an oddball task in which target stimuli having different characteristics between stimuli is recognized is often used.

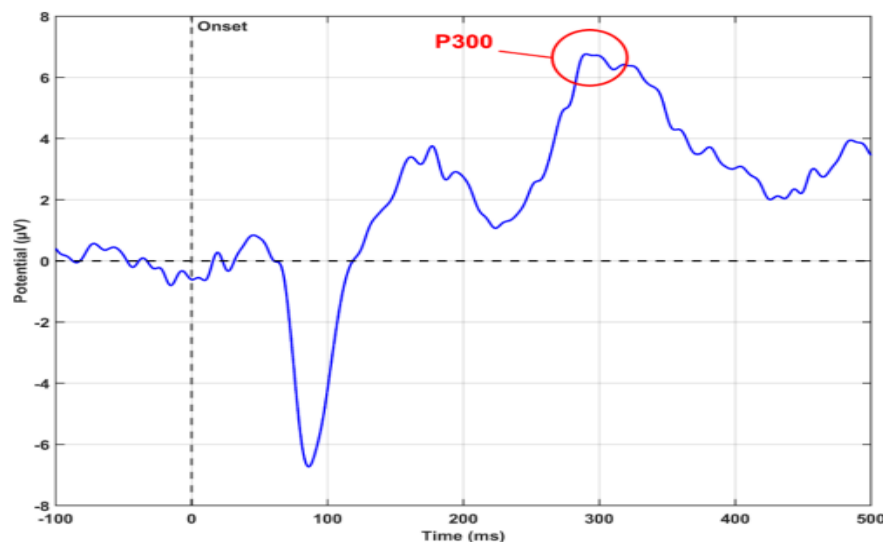


Figure 2. Derivation of P300 component of EEG

EEG activity is classified into evoked activity and induced activity. Evoked activity generally refers to activity that occurs when sensory processing is performed from external stimuli, and occurs at approximately the same time in all trials. On the other hand, since induction activity generally reflects the top-down mechanism of the brain, it is characterized by a different time point for each individual or each trial.

2.2.2 Frequency domain analysis method

EEG can be artificially divided into delta (< 4 Hz), theta ($4 \sim 8$ Hz), alpha ($8 \sim 13$ Hz), beta ($13 \sim 30$ Hz), and gamma (> 30 Hz) bands according to the range of oscillating frequencies. The criterion for dividing the frequency band may be different for each researcher, and there is no absolute criterion. These frequency bands are known to reflect different cognitive functions of the brain[23].

In order to analyze the frequency component of the EEG, the EEG must be converted into a frequency axis. Mainly, a frequency component of an EEG can be calculated through filtering, fast Fourier transform (FFT), and wavelet transformation (WT). Since actual EEG signals appear as a mixture of various frequencies, it is not easy to grasp information contained in EEG signals at a glance on the time axis. Therefore, researchers identify frequency components included in EEG signals through power spectrum analysis. Through this, the quality of EEG data is checked or simple information included in EEG is analyzed.

2.2.3 Time-frequency analysis method

The time-frequency analysis method has both time and frequency information of EEG signals. It is easy to determine which brain activity and frequency band are related. This time-frequency analysis can be analyzed through a short-time Fourier transform (STFT) or wavelet transform process. The short-time Fourier transform is suitable for real-time processing of EEG signals due to its relatively fast processing speed. However, since there is a trade-off relationship between the time resolution and the frequency resolution of the signal, one of the two must be abandoned[24].

In cognitive processing research, time-frequency analysis through wavelet transform is mainly used to compensate for the limitations of short-time Fourier transform. Because the Fourier transform uses a sine wave with no time constraint as a basis function to determine the correlation with the signal. However, since the basis function used for wavelet transform uses an arbitrary waveform satisfying only the corresponding frequency component with temporal weight as the basis function, it is possible to cope smoothly according to the time component and the frequency component.

2.3 Fuzzy technique

Fuzzy logic is a logic concept that expresses an ambiguous state or an ambiguous state as multivalued away from true or false binary logic. Fuzzy logic is a rule-based technology that can express imprecision by generating rules that use approximate or subjective values. These fuzzy theories are fundamentally different from probability theories. Fuzzy's principle states that everything is a matter of degree. Fuzziness refers to a spectrum of two or more, perhaps infinite choices. Fuzziness is not binary, but analog, which is an infinite gray density between black and white.

Recently, research on realizing functions close to human thinking ability by applying fuzzy theory has been actively conducted, and products applied to home

appliances and automatic control fields have appeared. After all, it is a technology for realizing an environment in which computers replace humans with the goal of automating human physical and cognitive labor, but it is by no means easily accessible. This is because most of human behavior uses a large amount of ambiguous information. In order to use ambiguous information for unambiguous work, it is necessary to convert the happenings into mathematical language so that the computer can understand itself. It is only when the numbers are calculated and the correct result is obtained that the computer performs a valuable action. At this time, the mathematical language to be changed must be a very precise number, and fuzzy theory demonstrates its skills in the process of reducing information loss by simplifying ambiguous expressions as much as possible.

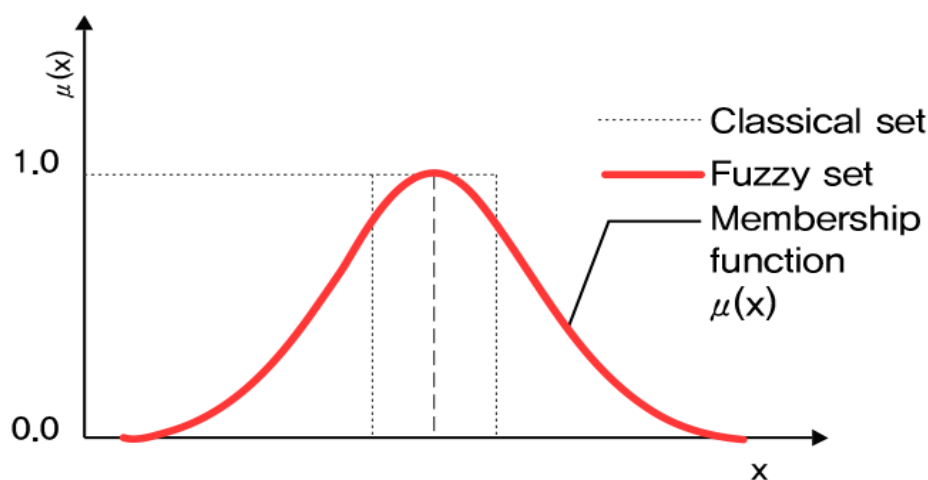


Figure 3. Examples of fuzzy sets and membership function

Figure 3 is a graph of an example of a fuzzy set and membership function. The concept of a fuzzy set expresses the degree to which each object belongs to the group from the binary logic that each object belongs to or does not belong to a certain group, that is, the degree of membership as a membership function. When a number appears, it should be possible to determine with certainty whether it belongs to or does not belong to the set. However, in fuzzy theory, it is also possible to discuss a collection of numbers for which the criterion for judging is not clearly set.

3. System Design

To implement a fuzzy-based EEG control system within a BCI environment, this study designed and developed a three-phase system encompassing signal acquisition, data preprocessing and model training, and mobile application deployment for virtual key control. Each phase is described in detail below.

3.1 EEG Signal Acquisition and Data Labeling

EEG signals were collected using the Emotiv EPOC+ headset, which features 14 channels arranged according to the 10-20 international standard (e.g., AF3, F3,

F4, FC5, etc.). The sampling rate was configured at 128 Hz, and data were transmitted wirelessly via Bluetooth in encrypted JSON packet format to a local PC. Decryption routines were implemented to convert packets into readable time-series data, which were then stored in .csv format for further processing.

Participants were instructed to gaze at virtual keys displayed on a screen for a fixed duration (4 seconds), with each key modulated to a distinct flickering frequency (e.g., 12 Hz, 15 Hz, 20 Hz) to induce frequency-specific SSVEP (Steady-State Visual Evoked Potential) responses. Behavioral observations and gaze fixation data were used to assign ground-truth class labels (e.g., "Key A", "Key B", "Rest").

Each EEG sample segment was 0.5 seconds in length, resulting in 64 time points per channel. A total of 2,000 labeled EEG samples were acquired, and stratified into training (60%), validation (20%), and test (20%) sets.

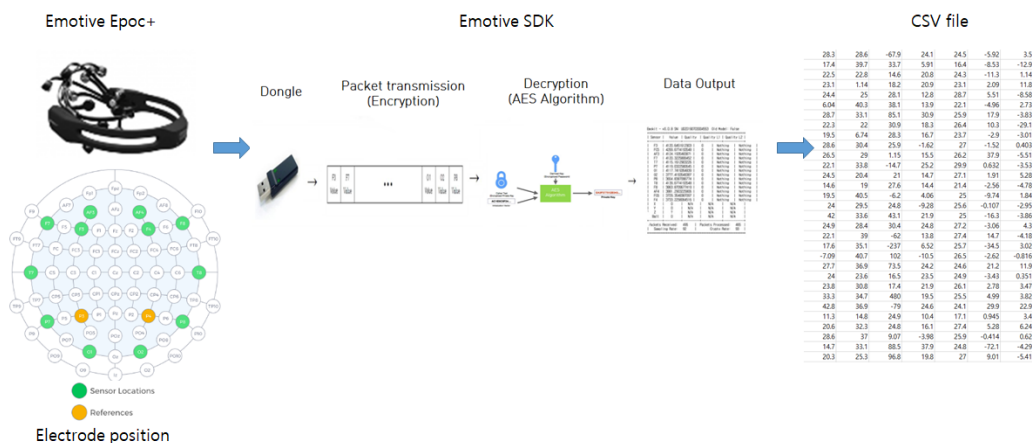


Figure 4. EEG collection and classification process design

3.2 EEG Preprocessing and Feature Transformation

In this study, a series of preprocessing steps were conducted to transform the raw EEG signals into a format suitable for deep neural network training. Initially, a bandpass filter ranging from 1 to 50 Hz was applied to eliminate low-frequency drift and high-frequency noise. To suppress power line interference, a 60 Hz notch filter was utilized. Furthermore, physiological artifacts such as eye blinks and muscle movements were removed using Independent Component Analysis (ICA), which isolates and eliminates artifact-related components from the EEG signal. After noise removal, the EEG signals were transformed into a frequency-domain representation. For this purpose, the Short-Time Fourier Transform (STFT) was employed, using a Hamming window with a window length of 128 samples and a 50% overlap. The resulting spectrograms were normalized using z-score normalization to stabilize the input scale, and then reshaped into 2D image-like data structures in the form of Channels $\times$ Time $\times$ Frequency, making them suitable for convolutional neural network (CNN) input.

In addition to frequency-domain representations, statistical features were extracted from the time domain to retain temporal information. These included the mean, variance, and skewness of the EEG signals for each time window. Furthermore, band power values corresponding to the five standard EEG frequency bands—Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (>30 Hz)—were computed for each segment.

This dual-stream approach, combining both spectrogram-based and statistical features, provided a comprehensive representation of EEG signals. It enabled compatibility with both deep learning and traditional machine learning classifiers and served as a robust input basis for comparative model evaluation. Figure 5 shows the process of processing EEG data.

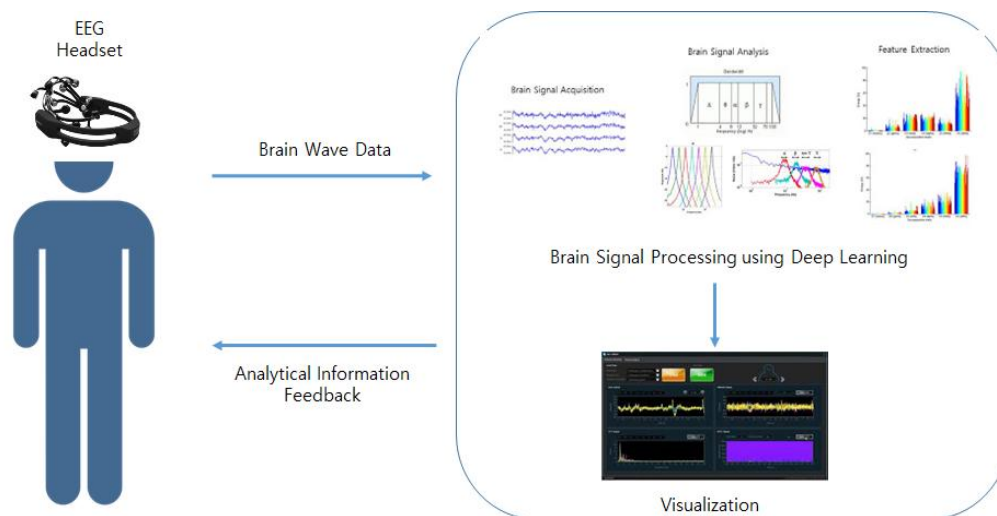


Figure 5. EEG data processing

3.3 Hybrid Deep Learning Model and Mobile Integration

To effectively classify user intentions based on EEG signals, a hybrid deep learning model was constructed by combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The CNN component was employed to capture spatial patterns across multiple EEG channels, while the LSTM component was designed to model the temporal dependencies inherent in sequential EEG data.

The CNN block consisted of two convolutional layers with 32 and 64 filters, respectively, both using 3×3 kernels and ReLU activation functions. Each convolutional layer was followed by a 2×2 max-pooling operation to reduce spatial dimensions and enhance feature abstraction. A dropout layer with a rate of 0.2 was applied to prevent overfitting. The output of the CNN block was flattened and passed to a bidirectional LSTM layer with 64 hidden units, which enabled the model to process EEG sequences in both forward and backward temporal directions. An additional dropout layer was included after the LSTM to enhance generalization performance. Following the feature extraction blocks, the model included a fully

connected layer with 128 units and ReLU activation, followed by a softmax output layer with four neurons corresponding to the four virtual key classes. The model was trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. Early stopping was employed to prevent overfitting based on validation loss. The training process was conducted over 20 epochs with a batch size of 16.

After training, the model was converted and deployed into an Android-based mobile application developed using Flutter and TensorFlow Lite. The mobile application received real-time EEG signals via Bluetooth Low Energy (BLE) from the EEG headset. When a user focused on a specific virtual key, the EEG signal corresponding to that key's flickering frequency was detected and analyzed locally on the mobile device. If the classification confidence exceeded a predefined threshold within a 4-second fixation window, the corresponding key event was transmitted to a connected secondary user, enabling real-time communication through a virtual keypad interface. The system was optimized to ensure a low-latency response, with the total delay from EEG signal acquisition to command execution measured to be under 1.2 seconds, which satisfies the practical requirements for interactive mobile applications.

4. Simulation and Discussion

Due to the non-linear, variable, and stochastic nature of brain signals, feature extraction and classification have traditionally relied on manual interpretation by experts. However, such manual processes are prone to errors, potentially leading to reduced accuracy in EEG analysis. To address this limitation, the present study adopts deep learning techniques—particularly a convolutional neural network (CNN)—for automated feature extraction and classification of EEG signals.

Among the models tested, the CNN demonstrated superior performance compared to both multilayer perceptron (MLP) and recurrent neural network (RNN) models. EEG data were collected 50 times per day across 5 days, resulting in a total of 1,000 labeled samples. Each sample consisted of a 0.5-second EEG segment, recorded at a sampling rate of 128 Hz using a non-invasive headset. The dataset was split into a training set (1,000 samples), a validation set (500 samples), and a test set (500 samples). The CNN model was trained with 20 epochs, a batch size of 10, and a dropout rate of 0.2. The network architecture comprised three convolutional layers, each followed by max-pooling, and three fully connected layers. The detailed structure is illustrated in Figure 6.

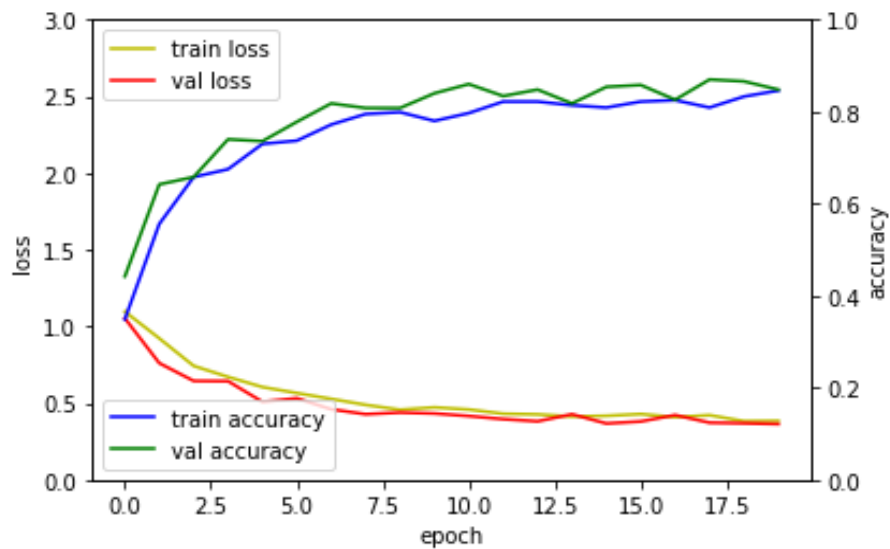
Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 128, 64)	256
dropout_1 (Dropout)	(None, 128, 64)	0
max_pooling1d_1 (MaxPooling1D)	(None, 128, 64)	0
conv1d_2 (Conv1D)	(None, 128, 64)	12352
dropout_2 (Dropout)	(None, 128, 64)	0
max_pooling1d_2 (MaxPooling1D)	(None, 128, 64)	0
conv1d_3 (Conv1D)	(None, 128, 64)	12352
dropout_3 (Dropout)	(None, 128, 64)	0
max_pooling1d_3 (MaxPooling1D)	(None, 128, 64)	0
dropout_4 (Dropout)	(None, 128, 64)	0
flatten_1 (Flatten)	(None, 8192)	0
dense_1 (Dense)	(None, 128)	1048704
dropout_5 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 128)	16512
dropout_6 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 3)	387
Total params: 1,090,563		
Trainable params: 1,090,563		
Non-trainable params: 0		

Figure 6. CNN model structure

In this paper, loss and accuracy were used as criteria for model validation. Accuracy means the accuracy of the model. It is close to 1, and the higher it is, the better the model is. In addition, since loss means the difference from the result value, the smaller the better. The CNN model used showed an accuracy of about 84%. Figure 7 shows the model performance evaluation by data type.

- Based on training data: loss: 0.3837 accuracy: 0.8460
- Based on verification data: loss: 0.3636 accuracy: 0.8480
- Based on test data: loss: 0.3348 accuracy: 0.845



```
860/860 [=====] - 0s 454us/step
## evaluation loss and_metrics ##
[0.3348772217801144, 0.8453488349914551]
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Figure 7. Evaluate model performance by data type

Figure 8 shows the system configuration for the development of a mobile control system between users based on EEG classification and quantification for design and development in the paper.

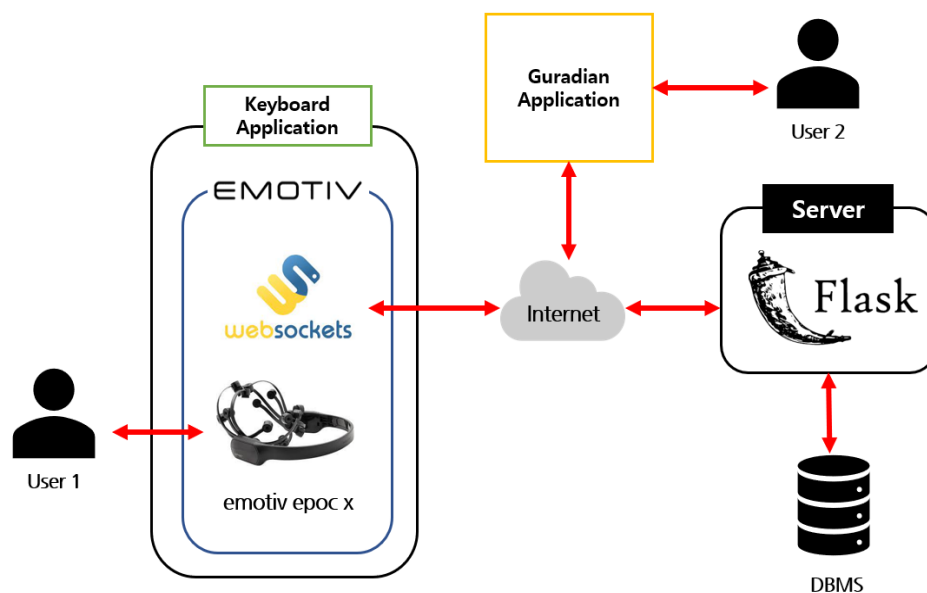


Figure 8. Mobile control and linkage system configuration diagram

When user 2 accesses the app, the linked device is searched. If there is no device list, you can use the app after proceeding with registration. Registration information is transmitted to the server and stored in a database. User 1 measures the EEG signals through the program and concentrates by staring at the key. When the key frequency matches the EEG, the value is sent to the server for analysis and forwarded to User 2's app.

Figure 9 shows a key-controlled mobile system through EEG measurement and classification. The left side of Figure 9 shows EEG analysis in a mobile environment through EEG measurements, and the right side shows EEG activation. First, the EEG analysis system in a mobile environment through EEG measurement outputs raw EEG as a line chart. In addition, states such as interest, stress, concentration, and stability were output as numerical values through EEG analysis. Next, EEG activation through the analyzed EEG was visually output. In EEG activation, EEG was activated and a range was output according to the position of the electrode. In addition, the EEG was divided into frequencies (Delta, Theta, Alpha, Beta, High Beta) using FFT (Fast Fourier Transform) and output as a bar chart.



Figure 9. EEG analysis(left) and activation(right) in a mobile environment

Finally, user 1 and user 2 are connected wirelessly, and virtual keys are controlled with EEG signals to enable mutual conversation. Figure 10 is a chatting implementation in a mobile environment by connecting a virtual keypad and EEG signals. The virtual keys output different frequencies and the user gazes at a specific key for 4 seconds. At this time, it was implemented so that the linked key is transmitted to the mobile system while the specific key and the EEG are linked.



Figure 10. EEG and virtual key linkage and mobile system control

5. Conclusion

Worldwide, Brain Computer Interface (BCI) is used for various medical purposes such as early detection of dementia, treatment of depression, and psychoanalysis, and furthermore, in numerous fields such as marketing and games. In addition, research using these bio-signals is a trend that is constantly being challenged and developed. Since EEG can display the current state of brain health and learning, it can detect slump, decline in grades, anxiety, lack of sleep, lack of concentration, ADHD, and depression. A brain-computer interface is a system that allows a user to communicate with an external device such as a computer without moving peripheral nerves and muscles. Thus, brain-computer interfaces are used in a variety of applications that allow people with movement disorders to interact with their surroundings.

To this end, in this paper, a system capable of measuring, analyzing, activating, and controlling EEG was developed by applying a fuzzy technique to minimize EEG measurement errors in the BCI environment. That is, a service platform has been developed in which different users connect their mobile devices to a wireless network and chat by controlling a virtual keypad through EEG signals. EEG was measured in a non-invasive way based on a headset, and pattern matching with virtual keys was analyzed by applying a CNN model to the measured EEG. In addition, the EEG measured in the mobile system was visualized and analyzed and activated. In a mobile environment, virtual keys output different frequencies and the user gazes at a specific key for 4 seconds. At this time, it is implemented so that the interlocking key is transmitted to the mobile system in a state in which the specific key and EEG signals are interlocked.

Through the technical results of this thesis, it is possible to know the condition and problems of the brain and train for improvement. In addition, it is possible to identify the most impressive scenes by analyzing the driver's sleepiness prevention solution that measures and warns the driver's drowsiness, games using EEG signals, and EEG signals when watching dramas, movies, or advertisements.

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