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Synesthesia-based Human Augmentation System for Brain to Brain Communication

Seung-Min Park[1], Mikyeong Moon[*2]

[1]Assistant Professor, Division of Computer Engineering, Dongseo University, 47 Jurye-ro, Sasang-gu, Busan 47011, KOREA
[*2]Associate Professor, Division of Computer Engineering, Dongseo University, 47 Jurye-ro, Sasang-gu, Busan 47011, KOREA
sminpark@dongseo.ac.kr[1], mkmoon@dongseo.ac.kr[*2]

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Abstract

The brain-computer interface (BCI) is slowly coming close to us, but there are still many technical challenges. We still don't know too much about the brain. To convert a pattern measured by the BCI to the information we can find out, we must find out how their neurons were firing in the brain, and what kind of pattern. The brain's pattern information is incredibly complex. For BCI to be the target whole-brain BCI, it must be able to precisely capture every single neuron in the brain and transmit it at the rate at which the brain's patterns ignite. In this paper, we proposed the core technology for communication between brains and brains instead of language-based communication by changing the communication method between humans from the existing communication methods (text, voice, video, etc.). In other words, we modeled synesthesia by analyzing the sense of the intention of the user to improve the efficiency of information transmission and respond to the objective action or emotional stimulus. We analyzed functional brain connectivity based on observational data on objective behavior. In this research, we visualized the brain connectivity and improved the way of expression by 89.05±1.96%. We proposed a synesthesia-based human augmentation system for brain to brain communication. 5-folds cross-validation based on functional brain connectivity was used to measure, predict and classify human responses in specific situations.

Keywords: *Synesthesia, Brain-Computer Interface, Human Augmentation System, Functional Brain Connectivity, Machine Learning*

1. Introduction

There is a lot of research underway to change the way people communicate with each other without simply giving order to machines. Recently, studies for further communication (brain to brain communication) between the brain and the brain in the way of communication between people is proceeding actively. Humans are said to sense 70% over time, the sense of the remaining 30% is to rely on other senses (hearing, touch, taste, smell). In most of the human sensory system, high dependence on the visual senses, including the new information by adding extraneous sense, that is by modeling synesthesia (synesthesia) engineered entered for this purpose act or emotional stimulation, increase the efficiency of information transfer. It analyzes the response to the user's intention recognized. Analyze functional brain connectivity based on observational data on objective behavior and use the information data received from a multi-modal sensor in a specific situation to respond to the user's intention information. It predicts, recognized through the observation data (sensor data-based synesthesia). Therefore, the goal is to ultimately increase the resolution of information in determining the corresponding viewer's response behavior. We think of this method as an extension of the existing ones into sensory communication, emotional communication, and motor communication. When

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conveying information by text or voice, we may feel a limitation in the power and speed of delivery. If communication between the brain and the brain is possible without going through an intermediary, information on sensory, emotional and motor data can be closely resolved, delivered in raw data, and the paradigm will change, and the speed of its development will increase with the generation of wireless communication that gets faster with generations. Furthermore, research on user movement (arm, leg, etc.) and emotion data-based intention recognition technology will be possible. In addition, intention response prediction and determination techniques using Recurrent Neural Network (RNN) based time series data will be studied. Research on various communication methods based on synesthesia is underway, and brain stem communication technology is being researched as a part of producing brain maps. This paper is organized as follows. Chapter 2 defines the contents and synesthesia about brainstem communication. In chapter 3, we propose a human augmentation system based on synesthesia and explain the experimental contents. Finally, chapter 4 consists of results and conclusions.

2. Related Works

2.1. Brain-Computer Interface

Brain-computer interface (BCI) is a technology that measures and analyzes the electromagnetic and chemical changes that occur in a person's brain to understand the person's intentions and controls electronic devices such as robots and computers[1]. This allows patients with quadriplegia who can't move their body at all, or who have no arms or legs, to use their own ideas to move the electric wheelchair, move the mouse cursor, type the keyboard, and move the robot's arms or legs to drink or move[2,3]. It is a technology that makes it possible. The big flow of BCI, as shown in Figure 1, first measures the activity of the brain and generates computer control signals through signal processing. First, the signal goes through a preprocessing process. The preprocessing process is easy to remove noise and perform basic signal processing. It is a process of re-referencing, high-pass, low-pass, band-pass, notch filter. Etc. After that, the feature extraction process is performed, and the process extracts features related to intention. For example, if you want to predict hand movements from electroencephalography (EEG), you can remove signals such as eye movements or brain responses

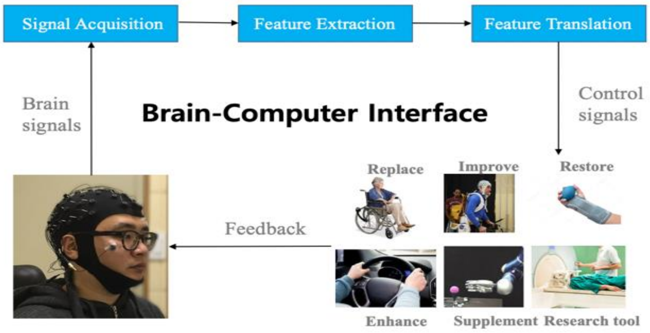

Figure 1. The concept map of brain-computer interface

to sounds and extract brain wave signals related to hand movements.

Principal component analysis (PCA), independent component analysis (ICA), and common spatial pattern (CSP) filters can be used to make relevant signals more pronounced or to reduce feature dimensions (reduce computations or reduce noise components). In some cases, the EEG signal may be used by using the power spectrum value or by down-sampling the EEG signal for the past several hundreds of ms[4].

When the feature is extracted, the intention is predicted based on the feature. We can predict the successive values or choose one of several choices. The former case is called regression, and the latter case is called classification. We can use the classification to distinguish between left and right, up, down, left and right, and select letters on the keyboard. Regression can be used to predict the movement of a continuous arm and control the robot arm as if it were your own. To achieve this, and to increase recognition rate, various researches and technologies are needed, including how to accurately measure brain activity, signal analysis, how to extract relevant features, how to classify and predict signals accurately, and how to control them accurately[5,6].

2.2. Synesthesia

Synesthesia is a phenomenon in which a stimulus evokes two senses at the same time. Synesthesia occurs due to the cross-activation of the brain sensory areas. This synesthesia is seven times more

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common in artists than in the general public. Some people claim that the source of creativity and artistry is synesthesia. If synesthetic thinking or synesthesia system is applied, it can be considered as the extensibility of information expression and interpretation of the new expression. The first way to train this synesthesia is to observe it. Look carefully at your own thoughts on how to look at things. Through constant observation of things, reprojection of the senses seems to be irrelevant. Beyond simply projecting other irrelevant sensations, they are recreated into a whole new sense of the sensation. The second is image shaping. Think carefully about what you think as if it really exists. When trained acquired and innate results are applied to a synesthesia architecture, a new dimension of information that we cannot hear or express can be created. The more expressive power of information (information resolution) can be seen, and information delivery power can also be tight. In other words, when you understand information, you will feel right about your body[7,8].

Brain to brain communication based on synesthesia is excellent in two ways compared to conventional communication. First is the throughput of information per hour, and second is the kind of information that can be communicated. We mostly type in the text when sending information. When we try to organize our daily routine and refine our thoughts, travel, or express thoughts to the outside, I usually use typing.

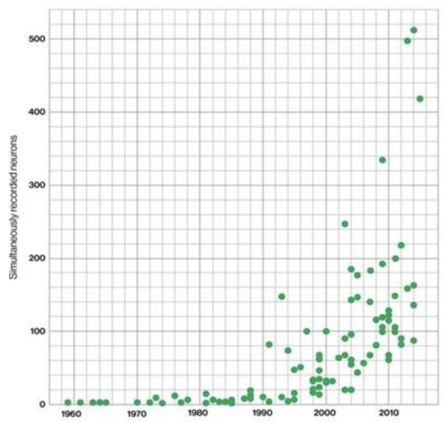

Figure 2. The Moore's Law of Brain-Computer Interfaces, the number of neurons recorded simultaneously from any animal's brain. Each point represents a published paper. (source : Ian H. Stevenson, UConn)

But this type of typing is much slower than thinking. The amount of information per unit of delivered while typing a character or are showing a lot of difference in the speed of delivery. Even for people who handle typing, especially, such as short hands, when they try to express what they think in real-time, the power of conveying information about the thought is ten times faster than typing. As the completion of Brain-Computer Interface (BCI) technology increases, we can communicate or control information at the speed of our thoughts. Much more information can be transmitted in unit time[9].

Figure 2 is a graph of the study's findings that the performance of brain-computer interface technology (increasing rate of neurons that can process simultaneously) follows Moore's Law[10]. As of 2010, the concentration of research as the environment of BCI technology evolved, and the personalization of computing power to process big data has been proved. At the time of becoming converted into the 4th Industrial Revolution, the research and development of the brain to communicate with the rapid development of artificial intelligence technology will also be an opportunity to step forward.

2.3. 5-folds Cross-validation

We require a data set for learning to create a regression, model-parameter estimation. When talking about regression performance, we use decision coefficients to analyze how well the dependent variable values in the training dataset are predicted. This performance is called in-sample testing.

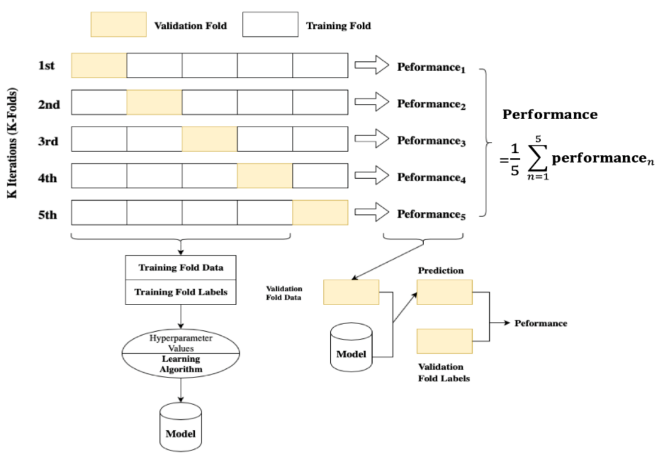

Figure 3. The 5-folds cross validation method

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One of the purposes of regression analysis is to find out the value of the dependent variable for a sample that is not yet known for the learning and therefore does not know the value of the dependent variable. This is called out-of-sample testing or cross-validation to check how well the dependent variable value of a set of sample data is not used for learning. Figure 3. is an understanding of 5-folds cross-validation.

2.4. Brain Connectivity

Brain connectivity refers to anatomical connectivity patterns ("anatomical connections"), statistical dependencies ("functional connections") between individual units of the nervous system, or causal interactions ("effective connections")[11,12]. Units are individual neurons, connected populations, or anatomically separated brain regions. Connection patterns represent statistical or causal relationships formed by structural connections, such as synapses or fiber pathways, or measured by cross-correlation, consistency, or information flow. Neural activity and extended neural cords are limited by connectivity. Therefore, brain connections are essential for explaining how neurons and neural networks process information.

Functional connectivity is fundamentally a statistical concept. In general, functional connectivity captures statistical independence between distributed and often spatially distant spaces. Statistical dependence can be estimated by measuring correlation or covariance, spectral consistency, or phase fixation. Functional connectivity is calculated whether or not it is directly connected between all the elements of the system. Unlike structural connectivity, functional connectivity is very time dependent. Statistical patterns between connecting elements fluctuate on multiple time scales, with some being as short as tens of milliseconds or hundreds of milliseconds. It should be noted that functional connectivity does not explicitly refer to a specific directional effect or underlying structural model [13,14].

3. Materials and Methods

3.1. Experimental Method

There is something to prepare for the experiment. In the case of subject experiments, it should be noted that a variety of variables can occur and can significantly affect the results of the experiment. Also, the experiment has always set the standard for the order, so that confirm the proposed process, in real terms, which can always be trusted to know in advance the expected results or waveforms, measure results.

3.1.1 BCI Competition IV Data set

There are many preparations and constraints when we do experiments with subjects. Most neuroscientists use data from a defined paradigm using reliable data. In this paper, we conducted a related study using dataset 1 of Graz University and dataset 1 of BCI competition IV.

3.1.2 Paradigm Design

These data sets were recorded from healthy subjects. In the whole session, motor imagery was performed without feedback. For each subject, two classes of motor imagery were selected from the three classes left hand, right hand, and foot (side chosen by the subject; optionally also both feet). In the first two runs, arrows pointing left, right, or down were presented as visual cues on a computer screen. Cues were displayed for a period of 4s during which the subject was instructed to perform the cued motor imagery task. These periods were interleaved with 2s of a blank screen and 2s with a fixation cross shown in the center of the screen. The fixation cross was superimposed on the cues, i.e., it was shown for 6s. These data sets are provided with complete marker information. Then four runs followed, which are used for evaluating the submissions to the competitions. Here, the motor imagery tasks were cued by soft acoustic stimuli (words left, right, and foot) for periods of varying length between 1.5 and 8 seconds. The end of the motor imagery period as indicated by the word stop. Intermitting periods also had a varying duration of 1.5 to 8s. Note that in the evaluation data, there are not necessarily equally many trials from each condition.

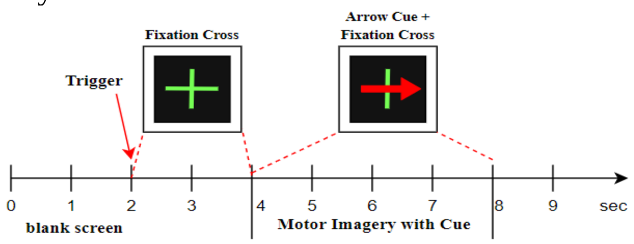

Figure 4. The motor imagery EEG experimental paradigm

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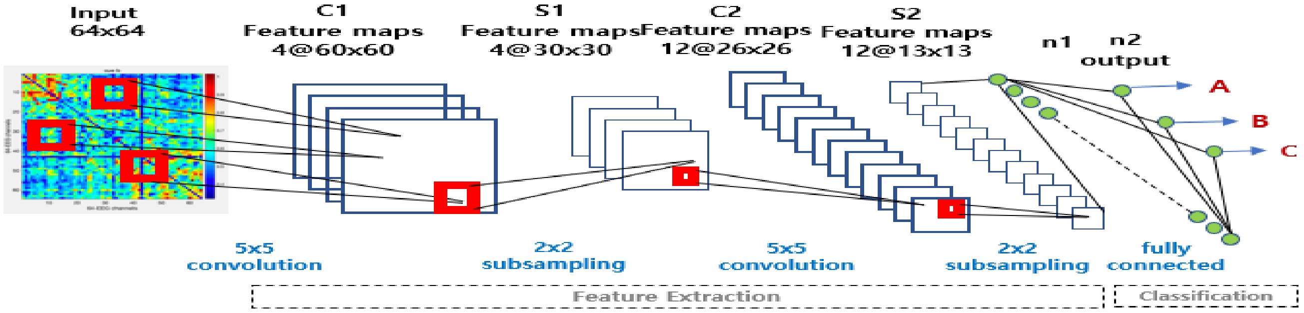

Figure 5. The detailed structure of convolutional neural network as the input signal

3.1.3 Protocol

The overall EEG measurement procedure is as follows. We acquire data for 64-channel EEG-based motor imagery using the BCI competition IV dataset. The functional brain connectivity is calculated from the data to form a mutual information matrix. Some mutual information matrix samples are needed in the learning phase of the data. The input mutual information matrix is used to parameterize the raw 64 channel EEG data and design the band-pass filter through the CAR algorithm. Then, labeling is performed for each stimulus, each epoch is extracted, and then brain connectivity is calculated and normalized to produce features.

An input signal of 64 x 64 was learning, and classification is based on the convolution of the structure in Figure 5. The data learning error was calculated using 5-fold cross-validation to increase the confidence level of the learning data and the dimension of the stimulus to classify according to the amount of data. The last layer of CNN in Figure 4 was composed of a softmax based fully connected layer. The final output value consisted of the type of stimulus we want to obtain, A (left hand motor imagery), B (right hand motor imagery), and C (foot motor imagery).

3.2. Experimental Results

We obtained a respective symmetric mutual information matrix from the seven subjects had been learning the characteristics of the CNN it to input matrix 64 x 64. More important than the number of subjects is to extract consistent data. Also, by the experiment in the same subjects, by a change in the subject state or time or environmental factors EEG because the data to non-stationary without depending on the absolute power and spectral values using the mutual information data of the brain connectivity analysis

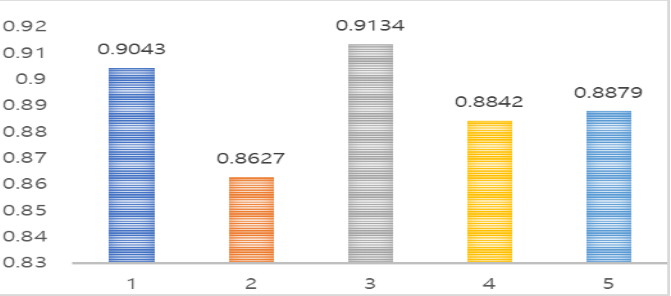

Figure 6. The results of 5-folds cross-validation scores

Figure 6 shows the results for 5-folds cross-validation. The five cross-validated scores were 0.9043, 0.8627, 0.9134, 0.8842, and 0.8879. The mean value was 0.8905, and the standard deviation was 0.0196. Concerning percentage, the result was 89.05$\pm\pm$1.96%.

Figure 7. is a result of the box plot using the results obtained in Figure 6. Currently, the chance level accuracy was 25%. It could be higher than the mean probability of occurring in a fortuitous opportunity to predict the performance of a single state from the three states and the reliability of the data.

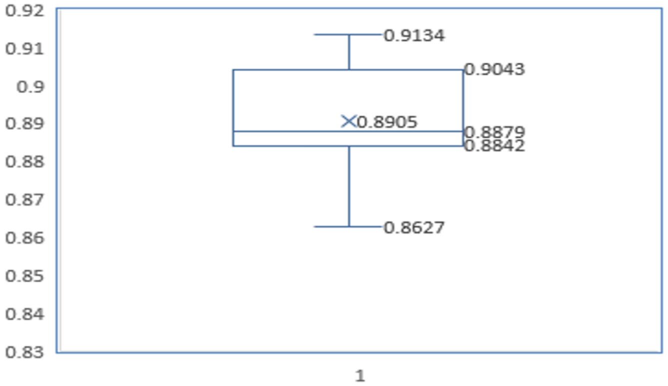

Figure 7. The accuracy of user intention recognition based on synesthesia

4. Conclusion

In this paper, we have developed an algorithm for estimating the three states of subjects by classifying them into convolutional neural networks by using mutual information based on synesthesia obtained from the EEG measured by the general population. It is expected that BCI technology will be put into practical use as a critical algorithm for BCI mode change. Analyzing brain activity using non-invasive methods of EEG is subject to a lot of trial and error. For example, it is essential to eliminate noise due to the reconstruction of the paradigm, the condition of the object, the temperature, and humidity of the shielded room. In this regard, the functional connection method using mutual information has an advantage of not relying on absolute power value or measured value because the correlation between domains is analyzed rather than an active state of a specific domain. Although the condition is not clear in all subjects, stimulus redevelopment methods and paradigms have also been able to achieve the expected results in some situations to discuss more predictable data. Functional brain connectivity changes with brain conditions. Predictions can be made using convolutional neural networks. In future research, mutual information is extracted through a convolution neural network in order to grasp the state of the user in real-time according to the change of EEG. We will develop a sequential data state prediction algorithm based on LSTM (Long Short-Term Memory network) of the recurrent neural network over time.

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