Investigation of Dynamic Transition of Learning Contents Based on Brain Waves

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Abstract: With the spread of the Internet, e-learning which is a way of learning using information technology has become popular. Although lecture videos in e-learning are designed so that many learners can understand, they do not take into consideration individual differences of learners. To address this problem, we designed a system that can grasp the concentration state of learners using electroencephalogram and dynamically provide contents according to the state. Moreover, we defined a metric using alpha waves in brain waves acquired from the occipital region as an index of changing learning materials used in the system. It enables providing suitable contents to each learner. In this research, we investigated the usefulness of the index and compared it with other brain waves such as theta waves and beta waves. As a result, it was confirmed that the proposed index was useful to extract learners who are relatively concentrating and not relatively concentrating. Moreover, it was suggested that alpha waves were more useful as the index for concentrating state than other waves.

Key Words: electroencephalogram, alpha waves, e-learning.

1. Introduction

Recently, the method of sharing knowledge is changing due to the digitization of things. Expressions on paper are decreasing because people come to use devices or displays to convey information. Especially in education, slideshows and animation videos are used in lectures instead of blackboards or handouts. Furthermore, the lecture video distribution system using the Internet has become popular, and it can remove restrictions on time and place. Although various learning systems have been developed, there are no systems that adapt to individuals dynamically. Conventional systems deliver the same learning materials to any learner regardless of the learner’s level. Learning systems should grasp a learning state such as how much the learner is concentrating and change learning materials dynamically depending on the learning state.

Nowadays, concentration measurement techniques using brain waves have been developed. However, there have never been systems that use the result for learning. Also, there is no index to classify learners based on the result of concentration measurement.

In this research, in order to solve the above problem, we designed a system that can grasp the concentration state of learners using electroencephalogram (EEG) and dynamically provide contents according to the state. We named the system providing knowledge dynamically using EEG from learner (OKAGE). Moreover, we defined $\eta$ using alpha waves in brain waves acquired from the occipital region as an index of changing learning materials. We evaluated the usefulness of $\eta$ through an experiment. In addition, we considered brain waves acquired from other parts of the brain and other frequency bands such as theta waves and beta waves, to confirm that using $\eta$ is optimal in OKAGE.

2. Related Work

2.1 Learning Contents

With the spread of the Internet, e-learning which is a way of learning using information technology becomes popular. E-learning makes it possible to digitize learning materials, take lectures remotely, and deliver lecture videos. E-learning systems are rooted in the concept of computer-assisted instruction (CAI) which aims to support the learning of statistics, physics, or mathematics using computers [1]. E-learning systems have evolved into various concepts such as learning management systems (LMS) or a massive open online course (MOOC). Especially in recent years, a MOOC has been mainly developed [2], which can diffuse learning contents to learners around the world via the Internet. Specialized learning fields can be recognized widely by integrating freely accessible online learning contents gathered from all over the world. It has been applied not only to educational institutions such as high schools and universities but also to specialized fields such as medical education field and astronomy [3],[4]. In a MOOC, learners cannot obtain knowledge interactively since there are no lecturers who can answer questions from learners in the system [5]. In addition, few studies adapt learning materials to each learner although some studies have researched a way to make learning materials that can adapt to all learners [6].

2.2 Brain Waves

Brain waves are signals of electrical activities generated by neurons. The signals can be converted into frequency bands shown in Table 1 by frequency analysis [7]. Theta brain waves are related to the subconscious mind such as sleeping and dreaming. Alpha waves are related to a relaxed state of mind.
Beta waves are associated with an active state of mind. Recently, brain waves have been studied widely to predict emotion or arousal [8],[9].

2.3 Measurement of Concentration

Brain waves have been studied for measurement of concentration. Measurement of concentration using brain waves is applied to a wide range of fields including fatigue of driver and effects of yoga [10]–[12]. Especially for education, it is used for evaluation of active learning which has attracted attention in recent years. In active learning, the teacher could not grasp all performance of students at the same time, and thus they evaluated the performance by receiving questionnaires from the students. However, this method has a problem that performance can only be evaluated subjectively. By measuring the concentration of the students using brain waves, they can evaluate the performance objectively [13]. Concentration measurement techniques have been exploited to evaluate learners, but no system adapts the subsequent learning materials to the measured results. Moreover, there is no metric to classify learners using the degree of concentration.

In this research, we propose a system that measures the degree of concentration and adapt learning materials to the measured result. The proposed system makes it possible to provide learning materials suitable for learners based on the objectively measured degree of concentration.

3. Design of OKAGE

3.1 Overview

OKAGE aims to change dynamically learning videos by estimating the learning state during watching a lecture video for a learner to receive a set of learning videos that are consecutive and appropriate for individuals. OKAGE adopts a client-server system since we assume that it is used in lecture video distribution service. Figure 1 shows the outline of the design. A learner watches lecture videos received from a server PC through a web browser on a client PC. While watching the video, OKAGE acquires learner’s brain waves using EEG and estimates the learning state on the client PC. The web browser decides a next lecture video depending on the result of learning state estimation, and then it gets the necessary lecture video from the server PC.

In conventional learning systems, the same lecture video is distributed to each learner, and thus there is a possibility that the lecture video might not be suitable for some learners. On the other hand, OKAGE can switch the current video to the appropriate video automatically during learning due to real-time learning state estimation using EEG.

3.2 Video Transition

Figure 2 shows a difference between conventional distribution systems and OKAGE. We assume that learners need to receive a learning unit to learn a subject. In OKAGE, a learning unit consists of several short videos. We refer to the order of learning videos in the unit as a learning path. OKAGE estimates the learning state at the end of each learning video and decides the next learning video according to the estimation result, in order to make branches of the leaning path. Making branches enables OKAGE to provide multiple paths for one unit. In this research, we focus on the concentration of learners and consider that learning videos are changed depending on the degree of concentration.

3.3 Degree of Concentration

We assume that learners cannot concentrate when they feel drowsy or want to rest. OKAGE uses a ratio of alpha waves as the degree of concentration because past studies have suggested that rest and closing eye are related to alpha waves [14],[15]. In addition, we assume that brain waves of learners are obtained during watching lecture video. If learners are attached to a lot of electrodes during watching lecture video, these electrodes can be inconvenient and disturbing for some learners. Hence, OKAGE needs to measure the degree of concentration using as few electrodes as possible. Since past studies have stated that closure of eyes and drowsiness induce occipital alpha EEG activity [16]–[19], brain waves of learners are obtained from the occipital region in OKAGE. In this research, we adopted a ten-twenty electrode system which is frequently used for the acquisition of brain waves. The electrode arrangement in the ten-twenty electrode system is shown in Fig. 3. In order to calculate the degree of concentration, brain waves at three channels O1, O2, and Oz which are placed in the occipital region.
are acquired. And then, signals from each channel are converted from the time domain to the frequency domain using fast Fourier transform (FFT). We defined the average ratio of alpha waves at channels O1, O2, and Oz as the degree of concentration $\eta$. When $\eta$ is high, we assume that the learner is not concentrating.

Assuming that subscripts for O1, O2, and Oz are 1, 2, and 3, respectively, the degree of concentration $\eta$ is expressed as follows:

$$\eta = \frac{S_1 + S_2 + S_3}{3},$$

where $S$ represents the sum of the absolute values of the frequency spectrograms of the alpha band, $T$ represents the sum of the absolute values of all the calculated frequency spectrograms.

4. Experiment

4.1 Experimental Method

In this experiment, we investigated a relationship between concentration and $\eta$ which is an index for the degree of concentration in OKAGE because we need to prove whether defined $\eta$ is practical. Additionally, we evaluated the usefulness of video transition. Finally, we researched brain waves acquired from each part of the brain and frequency bands such as theta waves and beta waves, to confirm that using alpha waves in the occipital region is optimal in OKAGE.

4.1.1 Subjects

We conducted an experiment for 22 learners. Eleven learners were given prior knowledge about a prepared learning unit, and the other 11 learners were not given it, to distinguish learners who can easily concentrate and learners who cannot. We named learners who were given prior knowledge and learners who were not given it as G1 and G2, respectively.

4.1.2 Learning videos

In advance, we prepared video A, video A’, and video B which are made from slide shows. In order to clarify the existence of prior knowledge, these explain neuron mechanism, which is a specialized unit. All learners were not specialized in the field. We used many technical terms such as neurotransmitter and action potential in video A, which are difficult for G2 to understand. As the prior knowledge, the G1 subjects took a five-minute lecture by a human teacher explaining the meaning of these technical terms before the experiment. Video A’ is a supplemental lecture video for video A, the goal of which is to deepen the understanding of video A using figures and animations. Example slides of videos A and A’ are shown in Figs. 4 and 5. The contents of Fig. 4 are better explained with an illustration in Fig. 5. The content of video B is created as the follow-on explanation assuming that the learner has understood the content of video A. Specifically, it explains how the excitement and inhibition of neurons affect the whole brain. The lengths of videos A, A’, and B are 196 seconds, 124 seconds, and 191 seconds, respectively.

Figure 6 shows the learning paths of the learning unit used in the experiment. We prepared path X to be played in the order of video A, video A’, and video B. And further we prepared path Y to be played in the order of video A and video B. We divided G1 into half and let each group take path X and path Y respectively. G2 was also divided into half and each group takes path X and path Y respectively.

4.1.3 Evaluation

In this experiment, we considered the following three perspectives.

1. Usefulness of $\eta$
2. Usefulness of video transition
3. Investigation on other frequency bands and other parts of learner’s brain for concentration

In consideration of (1), we observed a difference of $\eta$ between G1 and G2 during watching video A. We expected that $\eta$ of learners in G1 is lower than in G2 because slides which are comprehensible for G1 are prepared in video A and these are difficult for G2 to understand on the contrary. Finally, we discussed a threshold for video transition. In consideration of (2), we added six learners and we divided 22 learners into two groups using the threshold. We observed the change of $\eta$ from
video A to video B. And then, we considered which path is appropriate for each group. In consideration of (3), we investigated not only $\eta$ which is calculated from alpha wave of O1, O2, and Oz but also other parts of the brain and other frequency bands and consider whether these can be used as an index of concentration.

4.2 Experimental Environment

We used g.Nautilus manufactured by g.tec as EEG in OKAGE. It is shown in Fig. 7. All subjects were attached 16 electrodes.

We can select 250 Hz and 500 Hz as the sampling frequency of g.Nautilus. Because the frequency of the brain waves can be approximately 1 Hz to 64 Hz, we chose 250 Hz. Brain data obtained from g.Nautilus can be visualized and processed by Simulink which is a commonly used tool for dynamic simulation. In the experience, Simulink converted brain data from time domain into frequency domain. We analyzed the results using MATLAB.

5. Results and Discussion

5.1 Usefulness of $\eta$

Figures 8, 9, 10, 11, 12, and 13 show sample data of one of the learners in each group during watching video A for 30 seconds. The data was calculated every 0.5 seconds. Furthermore, Fig. 14 shows the graph of average $\eta$ during watching video A in each group. The average and the standard deviation of $\eta$ in G1 during watching video A were 0.191 and 0.0285 respectively. The average and the standard deviation of $\eta$ in G2 were 0.228 and 0.0371 respectively.

In the comparison of G1 and G2, we investigated whether the difference is statistically significant using a one-sided $t$-test. The significance level was set at 5%. The $p$-value was 0.043 which is lower than 0.05, thus it was confirmed that the difference between $\eta$ of G1 and G2 is statistically significant. Therefore, $\eta$ tends to be higher when watching a lecture video which is difficult to concentrate.

We determined a threshold of $\eta$ for video transition in OKAGE as $\eta_T$. Since the standard deviations were large, defining $\eta_T$ that classifies learners completely into G1 and G2 is difficult. Therefore, we calculated the range of value that G1 can take and the range of value that G2 can take using the averages and the standard deviations. We defined the average of $\eta$ in G1 and G2 as $\bar{x}_1$ and $\bar{x}_2$ respectively. In addition, we defined the standard deviation of $\eta$ in G1 and G2 as $s_1$ and $s_2$ respectively. Figure 15 shows the ranges. The range of $\eta$ in G1 was between 0.163 and 0.220. The range of $\eta$ in G2 was between 0.191 and 0.265. There is a region where the range of $\eta$ in G1 overlaps with the range of $\eta$ in G2. Because the region contains both many learners of G1 and G2, we cannot classify learners in the region into concentrating learners and non-concentrating learners. Hence, we assume that a learner is classified as a concentrating learner.
Fig. 14 Average $\eta$ in video A.

Fig. 15 Threshold for video transition.

Fig. 16 $\eta$ of non-concentrating learners.

Fig. 17 $\eta$ of other learners.

when $\eta$ is lower than the minimum of the range of $\eta$ in G1, and a learner is classified as a non-concentrating learner when $\eta$ is higher than the maximum of the range of $\eta$ in G2. Although we cannot classify all learners using $\eta$, we can extract learners who are relatively concentrating and not relatively concentrating.

In OKAGE, while path X which includes video A' is a supplementary path, path Y which delivers in order of video A and video B is a common path for the learning unit. In order to eliminate unnecessary video transitions, we focused on letting learners who are not really concentrating watch video A'. Thus, extracting learners who are not relatively concentrating is more important than extracting learners who are relatively concentrating. Hence, $\eta_T$ is set to 0.220 which is the maximum of the overlapping region.

5.2 Usefulness of Video Transition

We divided 22 learners into non-concentrating learners and other learners using $\eta_T$. As a result, there were nine learners whose average of $\eta$ exceeded the threshold, among which there were four learners who took path X and five who took Y. On the other hand, there were 13 learners whose average of $\eta$ did not exceed the threshold, among which there were eight learners who took path X and five who took Y. The average of $\eta$ in X and Y of each group is shown in Figs. 16 and 17.

We conducted one-sided $t$-test in each group in each path to investigate whether the differences between $\eta$ in video A and video B are statistically significant. The significance level was set at 5%. The results of the $p$-value are shown in Table 2.

As for non-concentrating learners, it was confirmed that the difference of only path X is statistically significant because the $p$-value of path X was 0.010 which is lower than 0.05. It suggests that path X is suitable for non-concentrating learners since the learners seem to be able to concentrate due to video A' in path X. As for other learners, it was confirmed that the differences between both paths are not statistically significant. Therefore, other learners should take path Y because video A' in path X does not affect the concentration of the learners and duration of path X is longer than path Y.

5.3 Investigation on Other Frequency Bands and Other Parts of Brain for Learner’s Concentration

In Section 5.1, we evaluated the usefulness of $\eta$ which is an index using the ratio of alpha waves at channels O. In Section 5.2, we also evaluated the usefulness of video transition by using $\eta$. However, there was a possibility that other frequency bands or alpha waves at other parts of the brain can be suitable for the degree of concentration. Therefore, we investigated alpha waves, beta waves, and theta waves at each part of the brain to search for the best frequency band and the best part of the brain for the degree of concentration. In this section, we used the data in Section 5.1.

The ratio of alpha waves, the ratio of theta waves, and the ratio of beta waves in each part of the brain during watching video A are shown in Tables 3, 4, and 5, respectively. Also, Figs. 18, 19, and 20 show parts of the brain where the ratio of each frequency band in G1 was higher.

Regarding alpha waves, G2 had a higher ratio than G1 at any part. In particular, the average of differences between G1 and G2 at channels O was large. As for beta waves, G1 had a higher ratio than G2 at channels O, P, C, and T. Particularly, the difference between the average of G1 and G2 at channels Fp was large. The theta ratio in G1 was higher than G2 at Fp1, Fp2, F3, P4, Pz. However, since the differences of theta ratio were small at any part according to Fig. 19, theta ratio is not suitable for the index which distinguishes learning states of concentration.

From the above, the average of the alpha ratio at channels
Table 3 Ratio of alpha waves in video A.

| Group | Cz | Fp2 | F3 | Fz | F4 | T3 | C3 | Fpz | C4 | T4 | P3 | Pz | P4 | O1 | O2 | Oz |
|-------|----|-----|----|----|----|----|----|-----|----|----|----|----|----|----|----|----|
| G1    | 0.195 | 0.124 | 0.161 | 0.174 | 0.163 | 0.161 | 0.175 | 0.126 | 0.186 | 0.159 | 0.204 | 0.210 | 0.194 | 0.187 | 0.193 | 0.192 |
| G2    | 0.222 | 0.152 | 0.189 | 0.202 | 0.196 | 0.199 | 0.208 | 0.152 | 0.223 | 0.188 | 0.231 | 0.234 | 0.238 | 0.234 | 0.229 | 0.221 |

Table 4 Ratio of theta waves in video A.

| Group | Cz | Fp2 | F3 | Fz | F4 | T3 | C3 | Fpz | C4 | T4 | P3 | Pz | P4 | O1 | O2 | Oz |
|-------|----|-----|----|----|----|----|----|-----|----|----|----|----|----|----|----|----|
| G1    | 0.212 | 0.217 | 0.216 | 0.214 | 0.212 | 0.190 | 0.209 | 0.220 | 0.205 | 0.176 | 0.199 | 0.202 | 0.200 | 0.183 | 0.188 | 0.187 |
| G2    | 0.219 | 0.203 | 0.212 | 0.225 | 0.217 | 0.210 | 0.212 | 0.207 | 0.213 | 0.199 | 0.204 | 0.198 | 0.200 | 0.187 | 0.186 | 0.185 |

Table 5 Ratio of beta waves in video A.

| Group | Cz | Fp2 | F3 | Fz | F4 | T3 | C3 | Fpz | C4 | T4 | P3 | Pz | P4 | O1 | O2 | Oz |
|-------|----|-----|----|----|----|----|----|-----|----|----|----|----|----|----|----|----|
| G1    | 0.285 | 0.189 | 0.240 | 0.259 | 0.245 | 0.283 | 0.285 | 0.187 | 0.287 | 0.295 | 0.297 | 0.309 | 0.310 | 0.316 | 0.305 | 0.314 |
| G2    | 0.262 | 0.233 | 0.267 | 0.251 | 0.260 | 0.262 | 0.274 | 0.232 | 0.266 | 0.276 | 0.273 | 0.282 | 0.276 | 0.286 | 0.298 | 0.299 |

Regarding beta ratio at channels Fp, the range that G1 can take overlaps largely with the range that G2 can take since the standard deviation of beta ratio at channels Fp was much larger than that of alpha ratio at channels O. It means that the range in which learners cannot be classified is large.

Therefore, using a one-sided t-test, we investigated whether the difference between G1 and G2 is statistically significant. The significance level was set at 5%. As for alpha ratio in O, the p-value was 0.043 which is lower than 0.05, and thus it was confirmed that the difference between G1 and G2 in alpha ratio at channels O is statistically significant. On the other hand, as for beta ratio at channels Fp, the p-value was 0.16 which exceeds 0.05, and thus it was confirmed that the difference between G1 and G2 in beta ratio at channels Fp is not statistically significant. From the above, using alpha ratio at channels O we defined as $\eta$ is better for the index of concentration than beta ratio at channels Fp.

### 6. Conclusion and Future Work

In this study, we designed OKAGE which is a system that provides learning materials suitable for the level of a learner by video transition depending on the learning state of the learner. In addition, we defined $\eta$ which is the ratio of the alpha waves at the occipital region. Then, we evaluated whether $\eta$ is useful as the index of the concentration state. As a result, although we could not classify all learners using $\eta$, we suggest that $\eta$ can be useful to extract learners who are relatively concentrating and not relatively concentrating. We also evaluated other frequency bands and other parts of the brain. We confirmed that the ratio of alpha waves at the occipital region which we defined as $\eta$...
is more useful than the ratio of other frequency bands and the ratio of alpha waves at other parts of the brain.

In this experiment, we used only two paths consisted of three short videos. However, the paths are insufficient to realize the provision of suitable lecture videos depending on the learning state of individuals. We need to prepare multiple videos such as advanced lecture videos and videos that encourage breaks. In addition, although the degree of concentration was used for classification of learners in the experiment, it is necessary to acquire how much the learner is understanding besides the degree of concentration to grasp learning state in detail.

Furthermore, although we focused on only learners, we should consider lecturers offering lecture videos. We need to design a simple way to create lecture videos with diverse paths so that many lecturers can provide a lot of knowledge.

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