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Effect of Teacher's Behavior on Students' Concentration Level

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Abstract

During lectures at universities and the like, teachers must devise ways to keep students concentrated and to ensure that they understand the taught material. However, even if this is the teachers' intention, it does not necessarily mean that the students are actually concentrated; the way teachers teach or the lacking interest of students can negatively affect their level of concentration. In fact, teachers cannot easily determine whether their students are concentrated during the lecture. In this study, we analyze the relationship among the students' concentration level, study material, and teacher's behavior. We provided nine one-hour Python programming classes in person. 38 students participated in the programming classes in all and each student attended up to three classes out of nine. In each class, three students were asked to wear electroencephalographs to measure their brain waves while the lecture was recorded on video. We collected 12 hours brain waves data and measured the concentration levels of the students based on the brain waves (i.e., the amplitude ratio between the beta and alpha waves) and their time differentials. Subsequently, we investigated how their concentration levels changed according to the study material and teacher's behavior. We discovered that the students' concentration levels are higher when the teacher is talking than when the students are having tests. Their concentration level increases when the teacher looks at them (i.e., away from the blackboard) or asks a student to answer a question. Based on these results, we present suggestions that help teachers maintain the student's concentration levels high during lectures.

Keywords: concentration level, electroencephalograph, alpha and beta waves, teacher's behavior, study material

1. Introduction

The purpose of this study was to determine how the concentration level of students changes in response to the teacher's behavior and the study material presented during a lecture. We performed experiments during actual lectures at a university and determined the indicators of what kind of study content we should provide and how teachers should behave in order for students to remain concentrated during lectures.

Normally, questionnaires are used in evaluations in educational settings [1]. However, evaluating the state of learners without their awareness and without distracting them while they are taking a class is difficult if only a questionnaire is used for the evaluation. Therefore, we conducted a quantitative evaluation with biometric information, i.e., we recorded electroencephalograms (EEGs).

Table 1: Study material and number of students during the lecture. Number in ( ) = number of students who were equipped with an EEG device and provided effective data

Class topic (year 2022)	Morning (11–12 AM)	Afternoon (1–2 PM)	Evening (6–7 PM)
1: (June 28) Control Syntax Basics	8 (1)	15 (1)	12 (0)
2: (July 5) Library	6 (2)	13 (3)	13 (1)
3: (July 12) Module	5 (0)	8 (1)	10 (3)

Section 2 presents related work based on EEGs and examples of the application of brain waves in the learning process. Section 3 describes the method of the experiments, and Section 4 presents the experimental results. Finally, Section 5 discusses the experimental results, and Section 6 provides a summary and the future challenges.

2. Related work

Researchers have proposed several methods for measuring the concentration level with EEG information [2-4]. Lokare et al. classified the concentration levels with the help of students' brain signals, which they recorded with EEG devices while the students performed different tasks that require different concentration levels [5]. Arana-Llanes et al. investigated the relationship between the concentration level and e-learning content [6]. These researchers measured the EEG information during lectures. However, they did not focus on the evolution of the concentration level during lectures and the relationship between the teacher's behavior and students' concentration level.

3. Methods

3.1 Experiments during lecture

The experiments were performed as supplemental courses to the Python Programming lecture/exercise course in the Information Technology department at the International Professional University of Technology in Tokyo. The supplemental courses were open to all second-year students of the same department (121 students in total). The study material was prepared in advance. The detailed lesson plan contained the course content, purpose of the research study, and ethical considerations. Thirty-eight students participated in the class.

3.2 Lesson plan

Each supplemental class lasted 60 min; they were held three times on June 28 (0628), July 5 (0705), and July 12 (0712), 2022; that is, nine supplementary classes were held during this period. Owing to the nature of the programming lecture and social distancing measures during the recent pandemic, there were morning (11–12 AM), afternoon (1–2 PM), and evening (6–7 PM) sessions; the 38 participants could attend the classes that were most convenient for them. Table 1 shows the topics of each day and numbers of students that attended each class. Since we could prepare for just three EGG devices, three students were equipped with the EGG device at each class. It was not mandatory for the students to attend all the classes on all three days. Therefore, the total number of students of each day is below 38 in Table 1.

3.3 Procedure of lecture

During each lecture, a brief 5 min review was presented, which was followed by a 5 min pretest and a 40 min lecture (which mainly involved the explanation of the confirmation test). Subsequently, a 5 min posttest was performed to determine whether the students had understood the content of the lecture. This was followed by a 5 min explanation of the posttest at the end of the lecture (Table 2).

Figure 1: Muse 2 (left) and EEG sensors of Muse 2 (right, TP9, TP10, AF7, and AF8)

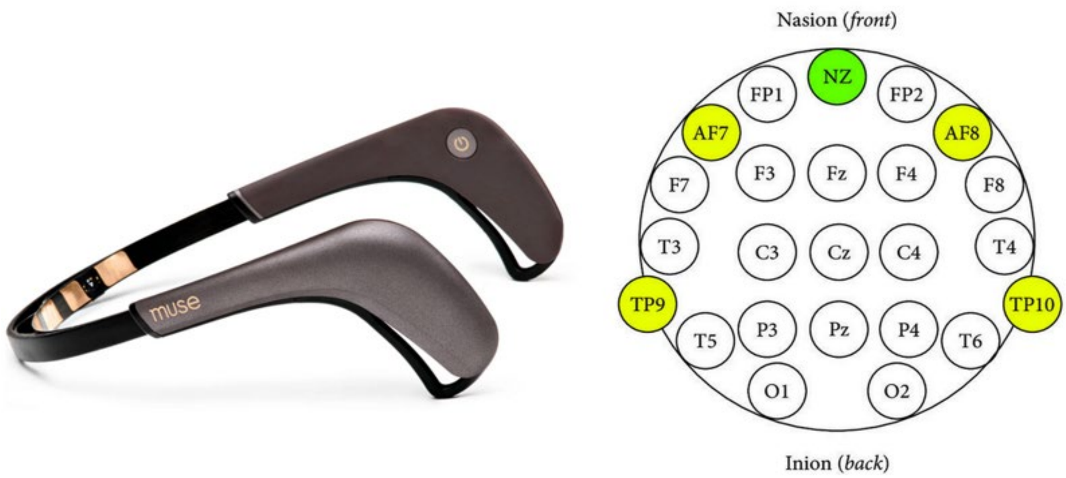


Table 2: Procedure of each lecture

Duration (min)	**5**	**5**	**40**	**5**	**5**
Part	"Before pretest"	Pretest	Lecture	Posttest	"After posttest"

Table 3: Characteristics of five basic brain waves

Frequency band	**Frequency**	**State of brain**
Gamma (γ)	>35 Hz	Concentrated
Beta (β)	12–35 Hz	Anxiety dominant, active, external-attention state, relaxed
Alpha (α)	8–12 Hz	Very relaxed, passive-attention state
Theta (θ)	4–8 Hz	Deeply relaxed, inwardly focused
Delta (δ)	0.5–4 Hz	In sleep

3.4 Method of EEG measurement

Table 3 shows the characteristics of the five basic brain waves [7]. The amplitude of the alpha wave indicates that he/she is very relaxed or in the passive-attention state; the amplitude of the beta wave indicates that he/she is in a predominantly anxious state, active, in the external-attention state, or relaxed. Researchers have shown that measuring the ratio of alpha to beta waves is an effective method for observing human concentration levels; the beta/alpha ratio is higher when the students are concentrated [8]. We use the beta/alpha ratio as the level of concentration.

Muse 2 (InteraXon) (Figure 1, left) [9], a smartphone (Google Pixel 4a), and the EEG raw data acquisition application Mind Monitor [10] were used to measure the EEGs of the students. During each lecture, three volunteer students wore Muse 2 for the entire time. Muse 2 is an EEG sensing headband that can be worn for long periods of time because it does not require electrodes or gels such as conventional biometric sensors. In addition, it is compliant with the international 10–20 method and can acquire 3D acceleration, 3D gyro, delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–35 Hz), and gamma (>35 Hz) wave information (Table 3) through its multiple electrodes (TP9, TP10, AF7, and AF8 [11]; Figure 1, right).

Figure 2: Overview of EEG data measurement

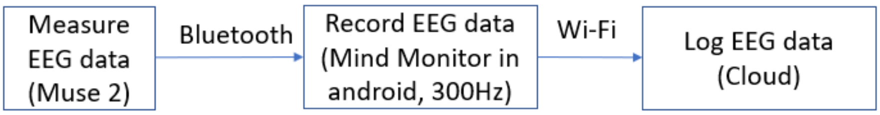
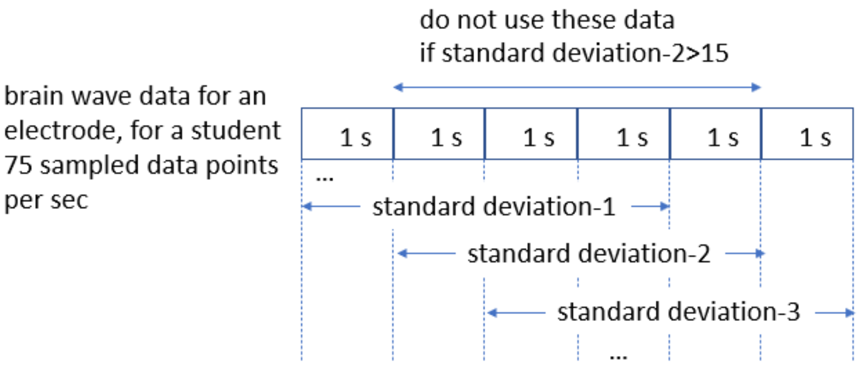


Figure 3: Calculation of standard deviation (sd); data are discarded if sd > 15



The data were recorded with the Mind Monitor application [10], which was downloaded in advance onto android smartphones; these were handed to each of the three students who wore Muse 2. The smartphones communicated with Muse 2 via Bluetooth, which sampled the brain waves at 300 Hz and recorded the data during the entire lecture. The data obtained by Mind Monitor were uploaded onto the cloud database via Wi-Fi (Figure 2).

During the lectures, the students and teacher were filmed with video cameras to determine the relationship among the brain waves and teacher and students' behavioral characteristics. The students and teachers were equipped with talk shields to facilitate facial recognition.

4. Experimental results

4.1 Preprocessing

The results of the EEG measurements presented in Section 3 were processed as follows [12]: First, the data sampled at 300 Hz were resampled at 75 Hz. Then, a band-pass filter with 5–40 Hz bandwidth was applied. Subsequently, the standard deviations of the output values, for raw EEG waveform data with units of μV (microvolt), of each electrode recorded within a 4 s window at 1 s intervals were calculated (Figure 3). Electrode data whose standard deviations were greater than 15 were considered noise (Figure 3). Data were discarded with respect to electrode data if less than 30 minutes of data remained after the removal of invalid data in one-hour class. The numbers in parentheses in Table 1 represent the number of students who provided effective measurement data for each lecture. Evidently, fewer than half of the group of participants provided effective data because the way in which some participants wore the Muse 2 headband was incorrect or there were communication errors between the Muse 2 and Android smartphone. The data of the evening on June 28 and of the morning on July 12 were not used because they were insufficient.

After preprocessing, the average of each electrode amplitude of each person that had been recorded each second was calculated; thus, the average of 75 data points was calculated because the data were resampled at 75 Hz. In addition, the average of the data from four electrodes in each second was calculated. When one or more of four electrode data were not useful because of large standard deviations or measurement errors, we calculated the average of the useful electrode data. Subsequently, the average of all the persons in each second was calculated.

4.2 Analysis results

The analysis was conducted by investigating two points: "1. The brain-wave level for each study material" and "2. The teacher's behavior in the moment in which the students' concentration levels were increasing".

Figure 4 shows the results of 1. (brain wave level measurement). For each class, the average amplitude of the alpha wave, beta wave, and concentration level (beta/alpha) for each class topic were calculated, i.e., before the pretest; during the pretest, lecture, and posttest; and after the posttest. The lecture was split into two parts (i.e., lecture-1 and lecture-2; each took 20 min) because this lecture was much longer than others. It was observed that the students were more concentrated during the lectures than during the tests. Moreover, it was observed that the alpha amplitude was low during the test, which is consistent with the report that alpha waves are particularly reduced in memory tasks [13]. However, since amplitude level of alpha wave was relatively low compared with that of beta wave, which is reported to change during concentration [14], the beta amplitude almost determined the concentration level. Figure 5 shows the average concentration level per date (left) and time zone of the lectures (right). The amplitude changes much on the early date (June 28) compared to afterward; no large difference can be observed for the time zone.

Table 4 shows the results of 2. (teacher's behavior to increase students' concentration level), with examples in which the average increase in the concentration levels of two or more students was large; the difference in the concentration level was recorded every second, together with the corresponding behavior of the teacher. Figure 6 shows a photograph of the teacher before and after a differential value of 0.485 was observed. Evidently, the concentration level increases when the teacher looks at the students (i.e., away from the blackboard).

Figure 4: Experimental results-1. Alpha wave (upper left, amplitude scale different from other graphs), beta wave (upper right), and concentration (beta/alpha) amplitude (lower right) per topic of lecture. Numbers "11", "13", and "18" represent lectures in the morning, afternoon, and evening, respectively

Figure 5: Experimental results-2. Concentration (beta/alpha) amplitude per topic, date (left), and time zone (right) of lecture. Numbers "11", "13", and "18" represent lectures in the morning, afternoon, and evening, respectively

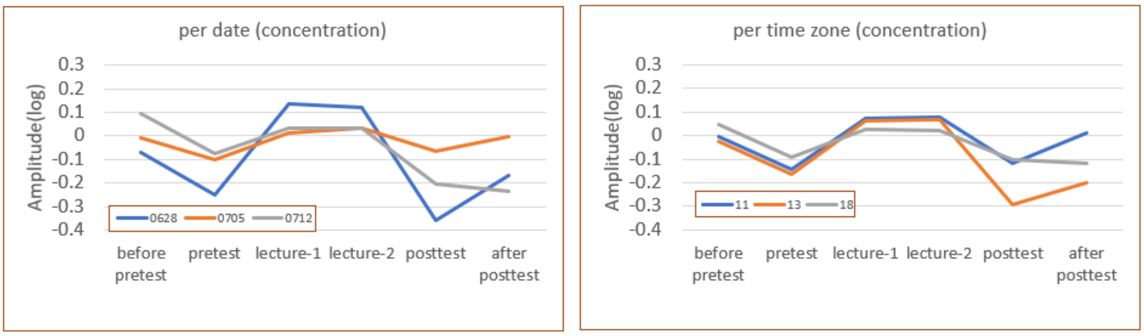


Table 4: Experimental results-3. Examples of teacher’s behavior while concentration level was increasing

d(log(β)/log(α))/dt	**Date/time zone**	**Topic (time point with respect to start)**	**Teacher’s behavioral characteristics**
0.485	July 12, 6–7 PM	Lecture-2 (47 min)	Turned toward students; is raising left hand to choose a student (Figure 6)
0.454	July 5, 1–2 PM	Lecture-2 (41 min)	Turned toward students and gazes at them for a second
0.446	July 5, 11–12 AM	Lecture-2 (49 min)	Turned toward students and gazes at them for a second

Figure 6: Behavioral characteristics of teacher: Before (left) and after (right) concentration level of students had increased

5. Discussion

In our previous experiments [15,16], we reported that concentration levels change in the classes according to the preferences of the subject, i.e. students were more concentrated for the preferred subjects. In this experiment, we investigated the concentration level from different approach, i.e., how concentration level changes by the structure of the class.

The experimental results indicate several trends. First, the students’ concentration level is relatively low during the test; on the contrary, it is increased while the teacher is giving the lecture. It is possible that the students’ concentration levels decrease during the test because they can answer the questions at their own pace. By contrast, while the teacher is talking, they are trying not to miss any detail and are afraid that they might be asked to answer a question at any moment; this increases their concentration level. The concentration level changed drastically with respect to the topic during the lectures on the first day (June 28) compared with those on the other days. It is possible that the students were relaxed before and during the pretest on the first day since they did not know what will be tested; after the test, the concentration level increased because they had discovered that they needed to know more than what they had expected; therefore, they listened more carefully to the teacher. On the second or third day, the students remained relatively relaxed during the lectures since they had become accustomed to them.

6. Conclusion and future work

During the experiments in the classroom, we observed changes in the students' concentration level as a result of the repetition of the tests and lectures and the teacher's behavioral characteristics. Since the concentration levels increased after the tests, performing tests during a lecture would help students maintain a high concentration level for an hour. Moreover, the teacher should look at the students and ask them questions to stimulate their concentration, in particular, at a later time during the lecture.

In this study, the levels of difficulty of the pre- and posttests were relatively low. In the future, we would like to study further the behavioral characteristics of teachers and their effects on the concentration level by investigating the relationship among the level of difficulty of the tests, the study plan and topics, and the concentration level.

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