Learning-State-Estimation Method Using Browsing History and Electroencephalogram During Programming Language Learning and Its Evaluation

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Abstract. The failure of learners to obtain sufficient knowledge is caused by various factors, such as the difficulty level and quality of the learning materials and learner's prior knowledge. The use of the learner's learning log and biological information, such as the brain waves, heart rate, and eye movements during learning, makes it possible to detect the factors. If different brain waves can be measured according to the difficulty level of task execution, the difficulty level of e-learning materials can be adjusted so that the optimum learning effect can be obtained for each student. In this study, a system that obtains the learning logs during learning has been proposed. However, the learning time is insufficient to understand the learning state of the learners. For example, if the learning time is short, whether the learning materials were too easy or too difficult to abandon cannot be determined. Therefore, we propose a system and a method for estimating the learning state of the learners by comprehensively analyzing his/her learning history and brain wave. Moreover, we evaluate the learning state of high school students learning the C and Scratch programming languages using the proposed method. Also, by comparing the estimated results with those obtained from the questionnaire administered after the experiments, we evaluate the effectiveness of our proposed method.

Keywords: Simple EEG · Brain wave · Learning analytics · E-learning.

1 Introduction

Currently, researches have been conducted to effectively apply web-based teaching materials to learning [1] and integrate digital textbooks and e-learning systems [2]. For a similar purpose, we developed a prototype of digital teaching materials and evaluated them in a classroom [3]. We also developed two systems that can extract the browsing history [4] and the editing history [5], respectively. We used these systems in both the English class [6] and programming class [7]. Numerous studies have been conducted to improve the coding skills of developers by analyzing the editing process of programming [8] [9].

During intellectual work, the brain waves were measured, and the *beta* waves were found to be strongly correlated with the person's mental state [10]. In previous studies [11] [12], it has been reported that the ratio of α waves to β waves effectively estimated the state of the human mind. We have experimentally confirmed that the ratio of low-β/low-α, in which "low" indicates low frequency, increases during the execution of difficult tasks [15] [16].

As previously mentioned, numerous researchers have proposed a system that can extract the browsing history, and they have used brain waves to estimate the state of the learner. However, just collecting the browsing history, such as the learner's browsing time, seems insufficient. For instance, when the browsing time is short, it is either that the learning materials are too easy for the learner or the learners have given up learning due to the difficulty level of the learning materials. Accordingly, we proposed a system to estimate the learning state of the learners through the integration and analysis of both the learning history and brain waves.

We evaluated the learning state of high school students who were learning the C [17] and the Scratch programming languages using our proposed method. Moreover, by comparing the estimated results with those obtained from the questionnaire administered after the experiments, we evaluated the effectiveness of our proposed method.

The remainder of this paper is organized as follows. In Section 2, we describe our previous work, and in Section 3, we discuss our proposed system and the method for estimating the learning state of the learners. In Section 4, we present the experimental methods and results. In Section 5, we analyze the estimation results obtained using our proposed method, as well as the questionnaire results. Finally, in Section 6, we summarize our study and discuss the future work.

2 Related work

2.1 Web-based learning-log-collection system

When we read the educational content in the PDF format on the web, the information "someone downloaded the PDF" is recorded, whereas the information that "someone looked at the x page of the PDF" is not. Thus, knowing exactly "which page of the PDF was viewed and how many times" is difficult for us as the browsing action for the PDF content is not recorded. In our previous study, we proposed a web-based log-collection system to support learning [4]. This system stores log information, such as learner ID, content number, page number, open and closed times, and number of seconds the page was viewed.

We have also developed an editing history visualization system [5] that collects not only the browsing logs but also the programming editing logs. It is a web-based system capable of collecting all the program codes during coding and visualizing the changed part of the program code. We can use this system to identify programming structures that is easy to make mistakes for programming beginners. We applied this system in the analysis of English learning [6] and programming learning [7].

Numerous studies have been conducted to improve the coding skills of developers by analyzing the editing process of programming. In [8] [9], other researchers have analyzed the coding process of 40 students using event logs during programming using a cloud-based programming development environment. They argue that by analyzing our proposed method, how to improve the coding skills of developers may be well understood.

2.2 Brain waves for learning

In previous studies, the learning state of the learners was estimated by measuring the α and β waves through the discrete Fourier change on the brain waves. Giannitrapani found that the low-β wave increases during intellectual work [10].

Uwano et al. have found that the ratio of the α and β waves can effectively estimate the learning state of the learners [11]. Conversely, Yoshida et al. found that a learner's learning state can be estimated by measuring the ratio of the α and β waves [12].

Some researchers have studied memory performance using brain waves. They found that the low-γ wave is an effective index for the measurement of memory performance [13]. The analysis results of the relationship between the low-γ wave (which reflects the memory work) and θ wave [14] revealed that the $(\theta+\alpha)/10$ wave and low-γ have synchronous wavelengths and that the $(\theta+\alpha)/(10 \times \text{low-}\gamma)$ ratio is an effective index for the measurement of memory performance. In our previous experiment, we employed a typing software that is capable of changing the difficulty level of the learning materials. We found that the β/α ratio increases during the execution of difficult tasks [15] and that the ratio of low-β/low-α affects the difficulty level [16].

To completely understand the characteristics of learners, several studies have been conducted to measure the brain waves during programming learning. In [18], researchers used EEG to directly evaluate the expertise of programmers. They proposed an approach for investigating expert knowledge in understanding programming languages. Moreover, in [19], researchers employed EEG to determine the differences between the beginners and experts in programming, both of which were found to exhibit different abilities in understanding the program. According to the EEG data, programming experts are excellent in understanding the programs.

3 Proposed system and method

Figure1 presents our proposed system that can be used to analyze the learning state of the learners. This system extracts the browsing logs from an existing learning-log-collection system and brain waves from an existing brain-wave-collection system. First, the browsing history obtained from the learning-log-collection system is stored via the learning-log-collecting part. Figure 2 presents an example of the browsing history log. For example, as presented in Fig. 2, a user called "ma001" read the seventh page for 49.3 s. Conversely, the brain waves obtained from the brain-wave-collection system is stored via the brain-wave-collecting part. Figure 3 presents an example of the brain-wave-collection log. For example, as presented in Fig. 3, the 11:30:21 α_l value of a user called "ma001" is 1097. The analysis part analyzes the learning state of each learner using the stored browsing history and brain wave information as well as stores the analysis results.

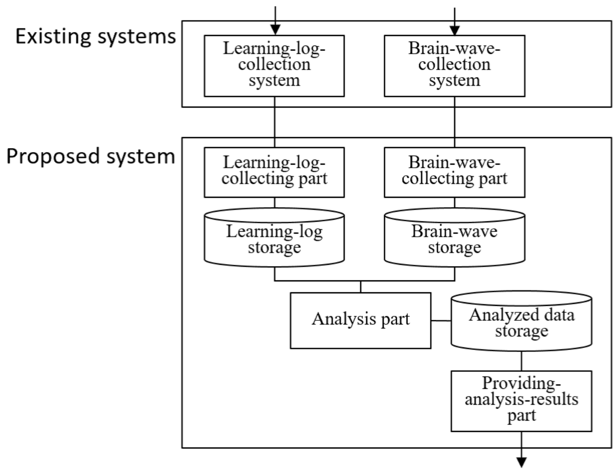

Fig. 1. Proposed system

```
userId=ma001 page=7 start=2016-06-12T11:05:53
end=2016-08-18T11:35:43 time=49.3
userId=ma001 page=8 start=2016-06-12T11:06:43
end=2016-08-18T11:36:06 time=22.9
userId=ma001 page=9 start=2016-06-12T11:07:06
end=2016-08-18T11:36:20 time=14.2
......
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Fig. 2. Example of browsing history log

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Date,userID,Page,Attention,Meditation,α1,β1
2016/08/18T11:30:21,ma001,3,56,41,1097,883
2016/08/18T11:30:22,ma001,3,70,23,138094,62256
2016/08/18T11:30:23,ma001,3,96,10,12529,22642
2016/08/18T11:30:24,ma001,4,100,1,3034,8763
2016/08/18T11:30:25,ma001,4,100,3,128468,7349
......
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Fig. 3. Example of brain wave log

A conventional method [12] that estimates the learning state of the learners by using a simple EEG has been proposed. With this method, whether the learner is solving a difficult problem or not can be determined. However, we cannot identify whether they have given up solving the problem or the problem is just too easy. In some cases, it is desirable to determine whether the learner understands the entire learning material or just a part of it. To solve these problems, we proposed an estimation algorithm.

Figure 4 presents the proposed method for the analysis conducted in the "Analysis part" of Fig. 1. First, the data indicating the degree of attention obtained from the EEG is used to evaluate whether "a learner cannot concentrate on learning (NC)" (Condition 1). We describe "attention" in detail in Section 4.3.

Next, based on the relationship between the degree of contemplation defined from the EEG value and the time spent browsing the teaching material, it is estimated whether the "content of learning is too easy (TE)" (Condition 2). Furthermore, using the same data as Condition 2, it is determined whether the "content of learning is too difficult (TD)" (Condition 3). Finally, using the number of page returns, it is estimated whether "there is a part that cannot be partially understood (PU)" (Condition 4). If all of the above conditions are not true, the learning state of the learner is estimated to be "a standard understanding state (ST)."

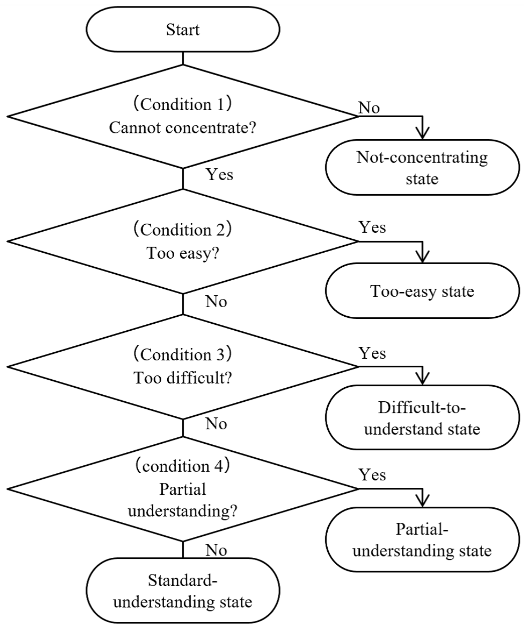

Fig. 4. Proposed method

Specifically, the algorithm works as follows. First, if the degree of attention of the learner is low, he/she is considered to have failed to concentrate using Condition 1. Next, using Conditions 2 and 3, it is determined whether the learners felt that the learning materials are too easy or too difficult. Although the difficulty level cannot be specified alone by the learning time, our proposed method adds brain wave information to the estimation formula to enable the estimation of the learner's condition. This makes it possible to distinguish between cases in which the learner needs time to think deeply (Condition 3) and cases in which taking time is not needed as the learning materials are easy to understand (Condition 2). If the learning materials are too difficult, the learner is considered to have lost concentration according to Condition 1. Finally, the learning state of the learner is estimated to be partially understood, depending on the number of times the page is returned in Condition 4. If Conditions 1 to 4 are not true, the learner's understanding is estimated to be standard.

4 Experiments

4.1 Outline of experiment

We held the “Matsudai Science Course” for the students in Matsudai High School in Niigata Prefecture and its neighboring high school and conducted experiments on the learning of the two programming languages, the C programming language (18 high school students) and the Scratch programming language (16 high school students). The experimental setup is presented in Fig. 5. All students were beginners in programming. Assuming the remote learning of blended learning and e-learning, the examinees were allowed to browse slides that explained the basics of the C and Scratch programming languages, during which we measured their brain waves. We used a part of the “Matsudai Science Course (9:00 AM to 15:50 PM)” to conduct experiments on the C and Scratch programming languages for 5 min each (10 min in total).

Fig. 5. Photograph of the examinees participating in the experiment

4.2 Browsing history acquiring method

In the experiments, we collected the learning history using the learning-log-collection system described in section 2.1. This system was used to collect log information, such as learner ID, content number, page number, open and closed times, and number of seconds the page was viewed. It is connected to the Moodle system, and by authenticating the user of the Moodle system, various log information can be obtained together with the authenticated user name. The study content included 8 slides about the C programming language and 16 slides about the Scratch programming language.

4.3 Brain wave-measuring method

The simple EEG we employed in our experiments is called the MindWave Mobile headset (NeuroSky, Inc.). This headset can detect potential differences (voltage) between the forehead (F_{P1} position of the international 10-20 system for EEG) and the ear (A_1 position), as presented in [20]. The signals are passed through low-pass and high-pass filters to retain signals in the range of 1–50 Hz. Aliasing correction, 128 Hz sampling, noise artifact detection and correction, and frequency component transform (fast Fourier transform (FFT)) were performed on the headset.

As presented in Fig. 6, after converting the brain wave data, the headset sends the data to the ThinkGear connector via Bluetooth. The log-collection system collects the brain wave data from the ThinkGear connector via the transmission control protocol/Internet protocol. The ThinkGear connector is a middleware driver provided by NeuroSky Inc., which is only used to transfer the converted EEG data within the headset to the user application.

The brain waves that can be obtained by the MindWave Mobile headset are presented in Table 1. The data that can be obtained is a 4-byte (unitless) floating-point value [21]. This headset can also collect attention and meditation values called eSense. These values are between 1 and 100 and are described as follows [22]: values between 40 and 60 are considered as neutral, those between 80 and 100 are considered as high, and those between 1 and 20 are considered as very low. Three types of data were used in the proposed method: α_l, β_l, and attention.

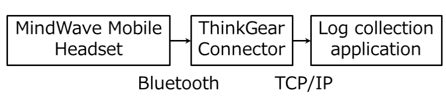

Fig. 6. Outline of the brain wave measurement

Table 1. Acquired brain waves

Type	Frequency (Hz)
δ wave	0.5–2.75
θ wave	3.5–6.75
low α (α_l) wave	7.5–9.25
high α (α_h) wave	10–11.75
low β (β_l) wave	13–16.75
high β (β_h) wave	18–29.75
low γ wave	31–39.75
mid γ wave	41–49.75

4.4 Experimental results

The browsing history logs of which pages the examinees viewed for how many seconds was collected. Moreover, the α and β waves and attention and meditation values were measured at 1-s intervals using a simple EEG. Since (low β wave)/(low α wave) represents the difficulty level of the task [16], we refer to that value of (low β wave)/(low α wave) as "contemplation degree."

5 Analysis of experimental results

Table 2. Estimated results obtained from studying the C programming language (based on Table 2 of [17])

ID	TM_i	T_i	$\overline{AT_i}$	$\overline{BW_i}$	B_i	$B_i + T_i$	P_i	Estimated results*				
ma001	154	-39.50	66.60	1.70	34.69	-4.81	3					ST
ma002	247	53.50	67.29	1.14	-21.50	32.00	11				PU	
ma003	225	31.50	43.19	1.45	9.90	41.40	4	NC		(TD)		
ma004	241	47.50	50.43	1.86	50.73	98.23	5			TD		
ma005	177	-16.50	57.21	0.94	-41.71	-58.21	4		TE			
ma006	231	37.50	44.06	1.37	1.95	39.45	7	NC			(PU)	
ma007	199	5.50	50.12	1.32	-3.55	1.95	0					ST
ma009	134	-59.50	50.78	1.88	52.62	-6.88	0					ST
ma011	98	-95.50	54.59	1.02	-33.49	-128.99	0		TE			
ma013	147	-46.50	66.97	1.16	-19.73	-66.23	0		TE			
ma014	168	-25.50	59.25	1.28	-7.27	-32.77	0					ST
ma015	243	49.50	65.75	1.34	-1.53	47.97	0			TD		
ma016	219	25.50	79.24	1.36	0.86	26.36	8				PU	
ma021	211	17.50	59.81	1.47	11.93	29.43	0					ST
ma022	283	89.50	30.25	1.26	-9.33	80.17	0	NC		(TD)		
ma023	158	-35.50	42.93	0.89	-46.34	-81.84	1	NC	(TE)			
ma024	133	-60.50	65.82	1.67	31.27	-29.23	7				PU	
ma026	215	21.50	46.52	1.26	-9.51	11.99	6	NC			(PU)	
Average	193.5	0.00	55.60	1.35	0.00	0.00	3.1					

* NC: non-concentration, TE: too easy, TD: too difficult,
PU: partial understanding, ST: standard understanding.
Symbols without () are the final estimated results.

5.1 Analysis results

Using the logs obtained as a result of the experiment, the learning state of the learners was estimated using our proposed method. The following formulas were used for the four conditions of the proposed algorithm:

$$\overline{AT_i} < 50 \quad \text{(Condition 1)}$$
$$B_i + T_i < -40 \quad \text{(Condition 2)}$$
$$B_i + T_i > 40 \quad \text{(Condition 3)}$$
$$P_i > 6, \quad \text{(Condition 4)}$$

Table 3. Estimated results obtained from studying the Scratch programming language

ID	TM_i	T_i	$\overline{AT_i}$	$\overline{BW_i}$	B_i	$B_i + T_i$	P_i	Estimated results*				
ma001	482	86.0	56.20	1.62	16.19	102.19	3			TD		
ma002	474	79.0	47.84	1.18	-27.48	51.52	1	NC		(TD)		
ma003	547	151.0	69.13	1.40	-5.73	145.27	5			TD		
ma004	575	179.0	45.24	1.10	-35.69	143.31	8	NC		(TD)	(PU)	
ma005	159	-237.0	49.19	1.54	8.27	-228.73	2	NC	(TE)			
ma006	351	-44.0	47.13	1.28	-17.71	-61.71	6	NC	(TE)		(PU)	
ma007	149	-247.0	36.55	1.24	-21.75	-268.75	1	NC	(TE)			
ma008	379	-16.0	64.82	2.24	78.59	62.59	2			TD		
ma009	512	117.0	46.49	2.01	55.35	172.35	1	NC		(TD)		
ma010	563	168.0	54.73	1.20	-26.32	141.68	4			TD		
ma011	438	42.0	58.83	1.39	-7.31	34.69	10				PU	
ma012	548	152.0	50.20	1.34	-12.03	139.97	8			TD	(PU)	
ma013	242	-154.0	63.44	1.63	16.67	-137.33	1		TE			
ma014	382	-14.0	55.43	1.15	-30.60	-44.60	5		TE			
ma015	318	-78.0	60.59	1.03	-43.35	-121.35	2		TE			
ma016	211	-184.0	58.60	1.99	52.88	-131.12	3		TE			
Average	396.0	0.0	54.03	1.46	0.00	0.00	3.9					

* NC: non-concentration, TE: too easy, TD: too difficult,
PU: partial understanding, ST: standard understanding.
Symbols without () are the final estimated results.

where

$$\overline{AT_i} = \Sigma_j AT_{ij}/n_i \tag{1}$$

$$B_i = 100 \times (\overline{BW_i} - \overline{BW}) \tag{2}$$

$$T_i = TM_i - \overline{TM} \tag{3}$$

$$\overline{BW_i} = \Sigma_j BW_{ij}/n_i \tag{4}$$

$$\overline{BW} = \Sigma_i \overline{BW_i}/m \tag{5}$$

$$\overline{TM} = \Sigma_i \overline{TM_i}/m, \tag{6}$$

where AT_{ij} denotes the attention of examinee i at time j; BW_{ij}, the β_l/α_l of examinee i at time j; TM_i, the reading time of examinee i; n_i, the number of measurement datasets from examinee i; P_i, the number of page-return times of examinee i; and m, the number of examinees.

Condition 1 is an expression determining whether the participants in the experiment were able to concentrate. The average value of the concentration of the participants was utilized for the judgment. Condition 2 is an expression determining whether the participants felt that the learning materials were too easy. We used the ratio of the α-waves and β-waves, which is said to indicate the degree of difficulty from previous studies, and the time to learn (read) the page. If the electroencephalogram value is low and the time is short, the learning materials are judged to be too easy. Condition 3 is an expression determining whether the participants felt that the learning materials were too difficult; the types of numerical values used are the same as in Condition 2. Condition 4 is an expression determining whether or not the learning materials are partially understood. The high number of participants returning to the previous page during the learning indicates that their understanding is partial. Therefore, we used the number of page returns as the conditional expression.

Tables 2 and 3 present the estimated results of the learning state obtained using the above formulas. Table 2 presents the results obtained from studying the C programming language, whereas Table 3 presents those obtained from studying the Scratch programming language. In the Estimated results column, the symbol without () indicates the final result. Conversely, the symbols with () indicate the possible estimated results other than the final result. The possible estimated results indicate the results that can be determined by the algorithm in Fig. 4, assuming that the above conditions are not satisfied.

5.2 Consideration on the validity of the experimental results

In this section, we statistically compare and analyze the results obtained from the questionnaires administered after the experiment with the learning state of the learners estimated using the proposed algorithm. The questionnaire items were as follows:

Q_1: Did you think the learning materials were easy to understand?
Q_2: Did you think the learning materials were difficult to understand?
Q_3: Did you concentrate during your studies?

The possible answers to each question item were as follows:

A_1: I agree.
A_2: I agree a little.
D_2: I disagree a little.
D_1: I disagree.

Questionnaire results obtained from studying the C programming language The questionnaire results obtained from studying the C programming language are presented in Table 4. Two examinees who were classified as TE (ma011 and ma013) completely understood (Q_1 was A_1) the learning materials and did not think that they were difficult to understand (Q_2 was D_1). Those classified as PU (ma002, ma016, and ma024) answered "Disagree" or "Disagree a little" in response to the item asking if the learning materials were difficult to understand (Q_2 was D_1 or D_2). This can be interpreted as having difficulty in understanding due to going back to the page and trying to understand because there were difficult parts. "Partial understanding" may also be interpreted as "there were parts that could not be understood at first, and understanding was deepened by page return." The examinees who were classified as TD (ma004 and ma015) responded that the learning materials were difficult to understand (Q_2 was A_1 or A_2).

Table 4. Questionnaire results obtained from studying the C programming language

ID	Estimated results					Questionnaire results		
						Q_1	Q_2	Q_3
ma001					ST	A_2	A_2	A_2
ma002				PU		A_2	D_2	A_2
ma003	NC		(TD)			D_2	A_2	A_2
ma004			TD			A_1	A_2	A_1
ma005		TE				A_2	A_1	A_2
ma006	NC			(PU)		A_1	D_1	A_1
ma007					ST	D_2	A_2	D_2
ma009					ST	A_2	A_2	A_1
ma011		TE				A_1	D_1	A_1
ma013		TE				A_1	D_1	A_1
ma014					ST	A_1	A_1	A_1
ma015			TD			A_1	A_1	A_1
ma016				PU		A_1	D_2	A_1
ma021					ST	D_2	A_2	A_2
ma022	NC		(TD)			A_2	A_2	A_2
ma023	NC	(TE)				D_2	A_2	A_1
ma024				PU		A_1	D_1	A_1
ma026	NC			(PU)		–	–	–

Questionnaire results obtained from studying the Scratch programming language The questionnaire results obtained from studying the Scratch programming language are presented in Table 5. Four examinees who were classified as TE (ma013, ma014, ma015, and ma016) completely understood the learning materials (Q_1 was A_1). All of them did not think the learning materials were difficult to understand (Q_2 was D_1), except for ma014. Two examinees who were classified as TE and NC (ma006 and ma007) completely understood the learning materials (Q_1 was A_1 or A_2) and did not think that they were difficult to understand (Q_2 was D_1 or D_2). Four examinees who were classified as TD (ma003, ma008, ma010, and ma012) responded that the learning materials were difficult to understand (Q_2 was A_2). There was only one examinee that was purely classified as PU (ma011), so it was difficult to analyze this result. The proposed method was effective for the estimated results of the TE, TD, and NC, as well as in the experiment involving the studying of the C programming language.

Statistical analysis In this section, we statistically analyze the results presented in Tables 4 and 5. In Tables 6, 7, and 8, the cross tabulation of the estimated results of our proposed method and the questionnaire results is presented. The numbers shown in the cross tabulations are the sum of the C programming language (Table 4) and the Scratch programming language (Table 5). Note that in Table 4, ma026 is not subject to statistical analysis due to the lack of questionnaire results.

We conducted a χ^2 test on the results presented in Table 9 and found significant differences in the Q_2 result.

Table 5. Questionnaire results obtained from studying the Scratch programming language

ID	Estimated results					Questionnaire results		
						Q_1	Q_2	Q_3
ma001			TD			A_1	D_1	A_1
ma002	NC		(TD)			A_1	D_2	A_1
ma003			TD			A_2	A_2	A_1
ma004	NC		(TD)	(PU)		A_2	A_2	A_2
ma005	NC	(TE)				D_2	A_1	D_2
ma006	NC	(TE)		(PU)		A_1	D_1	A_1
ma007	NC	(TE)				A_2	D_2	A_2
ma008			TD			A_2	A_2	A_2
ma009	NC		(TD)			A_2	A_2	A_1
ma010			TD			A_2	A_2	A_2
ma011				PU		A_1	D_1	A_1
ma012			TD	(PU)		A_2	A_2	A_2
ma013		TE				A_1	D_1	A_1
ma014		TE				A_1	A_1	A_1
ma015		TE				A_1	D_1	A_1
ma016		TE				A_1	D_1	A_1

Table 6. Crosstabulation of Q_1 results

	A_1	A_2	D_2	D_1
NC	3	4	3	0
TE	6	1	0	0
TD	3	4	0	0
PU	3	1	0	0
ST	1	2	2	0

Table 7. Crosstabulation of Q_2 results

	A_1	A_2	D_2	D_1
NC	1	5	2	2
TE	2	0	0	5
TD	1	5	0	1
PU	0	0	2	2
ST	1	4	0	0

Table 8. Crosstabulation of Q_3 results

	A_1	A_2	D_2	D_1
NC	5	4	1	0
TE	6	1	0	0
TD	4	3	0	0
PU	3	1	0	0
ST	2	2	1	0

In response to this result, we then conducted a residual analysis on the Q_2 result. With regard to reference, we also conducted a residual analysis on Q_1 and Q_3. The values of the adjusted standardized residual are presented in Tables 10, 11, and 12. The items in bold with "*" or "**" indicate significant differences (i.e., "*" indicates that the score is greater than 1.96 or lesser than -1.96, and "**" indicates that the score is greater than 2.58 or lesser than -2.58).

First, we consider Q_2 (Table 11), which was significantly different from the χ^2 test. The number of students classified as TE (too easy) who answered "A_2: I agree a little that the learning materials were difficult to understand in some places" is significantly low, whereas the number of those who answered "D_1: I do not agree that the learning materials were difficult to understand in some places" is significantly high. Although it was not a statistically significant difference, the number of students classified as TD (too difficult) exhibits an opposite trend from the number of students classified as TE. The number of students classified as PU (partial understanding) who answered "D_2: I do

Table 9. χ^2 test results

Qestion	p-value	Result
Q_1	0.1361 (> 0.05)	
Q_2	0.0205 (< 0.05)	Significant difference
Q_3	0.6919 (> 0.05)	

Table 10. Residual analysis of Q_1

	A_1	A_2	D_2	D_1
NC	-1.40	0.29	1.57	–
TE	**2.22***	-1.37	-1.26	–
TD	-0.34	1.29	-1.26	–
PU	1.13	-0.50	-0.90	–
ST	-1.38	0.18	1.68	–

* : $p < 0.05$, ** : $p < 0.01$

Table 11. Residual analysis of Q_2

	A_1	A_2	D_2	D_1
NC	-0.54	0.58	0.91	-0.85
TE	1.12	**-2.56***	-1.11	**2.67****
TD	-0.07	**1.75**	-1.11	**-1.04**
PU	-0.90	-1.83	**2.48***	0.91
ST	0.33	1.85	-0.90	-1.60

* : $p < 0.05$, ** : $p < 0.01$

Table 12. Residual analysis of Q_3

	A_1	A_2	D_2	D_1
NC	**-0.82**	0.54	0.63	–
TE	1.53	-1.20	-0.76	–
TD	-0.21	0.60	-0.76	–
PU	0.63	-0.38	-0.54	–
ST	-1.02	0.34	1.42	–

* : $p < 0.05$, ** : $p < 0.01$

not agree a little that the learning materials were difficult to understand in some places" is significantly high. As presented in section 5.2, this result is statistically supported by the fact that "partial understanding" should be interpreted as "there were parts that could not be understood at first, and understanding was deepened by page return."

Next, the χ^2 test did not exhibit any significant difference, but as can be seen from Table 10, the number of students classified as TE (too easy) who answered "A_1: I think that the learning materials were overall easy to understand" is significantly high.

Similarly, the χ^2 test did not exhibit any significant difference, but as can be seen from Table 12, the number of students classified as NC (non-concentration) who answered "A_1: I concentrate during my studies" is low.

6 Conclusion

In this study, we proposed a system to estimate the learning state of the learners through an integral analysis of the learning history and brain wave. We evaluated the learning state of high school students learning the C and Scratch programming languages using our proposed. Moreover, by comparing the estimated results with those obtained from a questionnaire administered after the experiments, we evaluated the effectiveness of our proposed method.

We have estimated the learning state of the learners for the entire learning time. However, we believe that by further estimating the learning state (e.g., for each page of the learning material), guidelines for the creation of learning materials can be provided. In our future work, we will establish a policy for setting the thresholds and coefficients of the four conditions in the proposed algorithm. Moreover, when estimating the learning state during learning, which involves editing texts, such as English and programming, rather than just browsing the teaching materials, this proposed method should be integrated with the editing history system. When the proposed method is employed in actual classes, we need to consider the validity of the learning contents, the learning conditions, and the educational curriculum, as well as the alternative devices to EEG, such as facial expression identification using a webcam. Furthermore, it is extremely important to compare and analyze the learning processes of text languages, such as the C programming language, and visual languages, such as the Scratch programming language. We believe that this analysis will be useful for beginners in programming languages to achieve a smooth transition from learning visual languages to text languages.

Research ethics

The Research Ethics Committee of Shonan Institute of Technology has approved these experiments. We also have received consent to participate in this experiment from participants and their parents.

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