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Comparison Experiment of Learning State between Visual Programming Language and Text Programming Language

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Abstract—Recently, visual programming languages such as Scratch have been popular among novice programmers. Afterward, they employ text-based programming languages such as C and Java. Nevertheless, there are significant barriers between visual and text-based languages. Thus, it is important to establish a seamless transition from visual to text-based languages. In this study, we clarify the difference in the learning process between visual language and text-based language by measuring brain waves. Specifically, experiments will be conducted to solve problems with various difficulty levels for learning visual and text-based languages. The brain waves will be measured, and the values of β/α will be evaluated. Results show that the values of β/α when solving difficult problems increased in the text-based language, but not in the visual language. This suggests that beginners may be thinking differently in the learning process of visual and text-based languages.

Keywords—programming, learning state, visual language, text language, learning analytics

I. INTRODUCTION

Recently, a visual programming language (hereinafter visual-type language) is being used as an introduction to programming. Then, the learner migrates to a text-type programming language (hereinafter text-type language) such as C or Java programming language. However, no seamless transition method has been established.

The purpose of this study is to establish a methodology for the transition from visual-type language to text-type language. Once this research is established, programming language beginners will start learning visual-type languages and effortlessly and spontaneously transition to learning text-type languages. This is a critical study that will help programming instructors handle difficulties that they will encounter in the future.

In our previous study [14], brain waves in the learning of visual-type language (Scratch) and text-type language (C language) were measured. Consequently, we questioned whether the brains that humans use to learn visual-type and text-type languages are different.

In this study, we clarified the difference in the learning process of visual-type and text-type language by measuring brain waves. Specifically, experiments were conducted to solve problems of various difficulty levels for learning visual-type and text-type languages, brain waves were measured concurrently, and β/α values evaluated.

Section 2 provides an outline of related works; Section 3 describes the participants of the experiment, the tasks used in the experiment, and the experimental method; Section 4 shows the experimental results, and the discussion is given in Section 5, and Section 6 presents the conclusion of the work.

II. RELATED WORK

A. Visual-type language and text-type language

Visual-type languages fall into two major categories: block-type imperative languages and flow-type functional languages.

Mason et al. conducted hundreds of experiments to program simple problems designed to be similar in the two categories of block-type and flow-type languages. They conducted an empirical study to evaluate the relative benefits of the two categories [1].

Mladenović et al. surveyed student misunderstandings on loops, one of the basic concepts of programming, in 207 elementary school students. The students learned three programming languages: a block-type language (Scratch) and a text-type language (Logo and Python). They observed that block-type languages minimized misunderstandings about loops. This difference became more obvious as tasks became more complex, such as nested loops. The legitimacy of employing a visual language for programming beginners is argued in this study since it does not generate syntax mistakes [2]. However, there is no mention of bridging the gap between the two languages in this study.

Daskalov et al. proposed an environment for beginners to use a hybrid-type language of text-type and visual-type languages. It is a hybrid-type environment of flow-type visual language and text-type language instead of block-type

language and claims to be suitable for training novice programmers [3].

Weintrop compared text-type, visual-type, and hybrid-type languages. In conclusion, while hybrid-type languages showed characteristics of both text-type and visual-type languages, they also demonstrated that hybrid-type languages outperformed block-type and text-type languages in certain dimensions [4].

Tóth et al. highlighted the existence of a gap between visual-type and text-type languages. They observed the migration from a visual-type language (MIT App Inventor 2) to a text-type language (Android Studio) using Java Bridge Code Generator as a mediator of knowledge transfer. They claimed that the gap between visual-type and text-type languages was bridged by the Java Bridge Code Generator [5].

B. Browsing history/editing history system

Aramoto et al. proposed a web-based browsing history visualization system that collects the browsing history of PDF contents [6]. In addition, they developed an editing history visualization system that collects not only browsing history but also programming editing history [7]. Nakano et al. [8] applied this system to English learning, whereas Goto et al. [9] applied it to programming learning and experimentally evaluated the effect. In addition, sufficient studies have been conducted to improve developers' coding skills by analyzing the editing process of programming [10] [11].

C. Application of brain waves to learning

Giannitrapani estimated the learner's learning state by measuring the α and β waves obtained by performing a discrete Fourier transform on the brain waves. Here he observed that low beta waves increased during intellectual work [12]. Uwano et al. also discovered that the ratio of α waves to β waves can effectively estimate the learner's learning state [13]. Yoshida et al. also showed that the learner's learning state can be estimated by measuring the ratio of α waves to β waves [14]. In our previous experiment, we used a typing software that can change the difficulty level of the learning material and observed that β/α increased during the execution of difficult tasks, and confirmed that low- β /low- α affected the difficulty level [15] [16].

To better understand the characteristics of learners, several studies have been undertaken to monitor brain waves during programming learning. Crk et al. used electroencephalograph (EEG) to directly measure programmer expertise. They proposed a basic approach for investigating the role of expertise in understanding programming languages [17]. Lee et al. also used EEG to observe the difference between programming beginners and experts. They deduced from EEG data that programming experts have excellent abilities in understanding programs [18].

III. EXPERIMENT

A. Experiment participants

We hosted a "Matsudai Science Course" for high school students in a neighborhood, mostly Matsudai High School students from Niigata Prefecture, and an experiment was conducted in the science course [19]. Seven students participated in the experiment using a visual-type language

(Scratch), whereas nine students participated using a text-type language (C language). The text-type language experiment was conducted using two sets of easy and difficult problems.

B. Task

Figs. 1 and 2 show the tasks used in the experiment of visual-type language (Scratch), whereas Figs. 3–6 show the problems of the text-type language (C language).

Let's create a program that meets the following conditions.
When you press the up arrow key, "Saru-kun" moves upward on the stage.
Conversely, when you press the down arrow key, "Saru-kun" moves downward on the stage. In both cases, the amount of movement is equivalent to 10 in coordinate values.

Fig. 1. Easy Question of Visual Language (Scratch)

Let's add the following functions to the program in question above.
When you click the flag, "Cat-chan" keeps moving in the left-right direction (horizontal direction).
"Cat-chan" bounces back when it reaches the left and right "edges".
"Cat-chan" moves as if walking.
When "Saru-kun" hits "Cat-chan", he says "I was killed"
When "Saru-kun" can touch "Banana" safely, the banana is hidden.

Fig. 2. Difficult Question of Visual Language (Scratch)

(After showing an example that repeats 5 times)
Modify the "for" statement in the example and create a program to repeat it 10 times and execute it.

Fig. 3. Easy Question 1 of Text-based Language (C Language)

There is a program that displays "1st repeat", "2nd repeat" ... "10th repeat".
Create and execute a program that modifies this so that it is displayed as "10th repeat", "20th repeat" ... "100th repeat".

Fig. 4. Difficult Question 1 of Text-based Language (C Language)

(After showing an example of finding the sum of up to 10)
Create and execute a program that calculates the sum of 1 to 100 and displays the calculation result.

Fig. 5. Easy Question 2 of Text-based Language (C Language)

The expression $i \% 2 == 1$ means "the remainder of dividing i by 2 is equal to 1." In other words, " i is an odd number". Use this fact to create and execute a program that calculates and displays the sum of odd-numbered values from 1 to 100.

Fig. 6. Difficult Question 2 of Text-based Language (C Language)

C. How to measure brain waves

The EEG was measured using a NeuroSky EEG control MindWave® Mobile headset. The log collection application collects brain wave logs via TCP/IP communication with ThinkGear Connector after connecting the headset and connector via Bluetooth. The ThinkGear Connector is a driver that provides a communication function with the

MindWave Mobile headset provided by NeuroSky Inc. In addition, the types of brain waves that can be acquired are the eight types shown in Table I, and each value is a 4-byte floating-point number without a unit [20].

As shown in Table I, the EEG used for this measurement measures two types of brain waves: high frequency and low frequency for α and β wave, respectively. In particular, when considering β/a , which is the ratio of α wave to β wave, four types of combinations of β_l/α_l , β_h/α_h , β_l/α_h , and β_h/α_l can be considered. In addition, the average ratio $(\beta_l + \beta_h) / (\alpha_l + \alpha_h)$ of low frequency and high frequency (hereinafter β_{l+h}/α_{l+h}) was added, and we focused on all five types of β/a .

TABLE I. THE KIND OF BRAIN WAVES WHICH CAN BE ACQUIRED

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

IV. EXPERIMENTAL RESULT

In the experiment, the brain waves at 1-s intervals were initially measured while each participant was solving the task. Then, various β/a per second, that is, five types of β_l/α_l , β_h/α_h , β_l/α_h , β_h/α_l , and β_{l+h}/α_{l+h} were calculated. The average of various β/a values while solving the task was calculated. The calculated average values are shown in the Tables V to X in the Appendix.

Tables II, III, and IV show the ratios of various β/a values when solving easy and difficult tasks. For example, an numerical value in a cell in Table II show the results of division between the numerical values in the cells at the same location in Tables V and VI in the Appendix. The value of the gray shaded cell shows 1.00 or more. The numerical values marked with * represent the significant numerical values (p -value ≥ 0.05) at the significance level of 5% in the t -test (test of the difference between the average values). Moreover, it showed that this average value was considered different. In particular, the gray shaded areas marked with * indicate that the average β/a values were statistically higher when solving difficult tasks. However, the part marked with * without gray shading indicates that the average value of β/a was statistically lower when solving a difficult task. The specific values of the p -value are shown in Tables XI to XIII of the Appendix.

TABLE II. RATIO OF "DIFFICULT" TO "EASY" IN VISUAL LANGUAGE

ID	β_l/α_l	β_h/α_h	β_l/α_h	β_h/α_l	β_{l+h}/α_{l+h}
ma002	1.051	1.041	1.069	1.040	1.047
ma004	0.814	1.047	1.007	0.877	0.976
ma006	0.932	0.739*	1.020	0.759*	0.909
ma008	0.822	0.886	1.016	0.703*	0.869*
ma011	0.852	0.771*	0.983	0.651*	0.805*
ma013	0.832	0.875	1.081	0.691*	0.879
ma016	0.861	0.943	1.021	0.791	0.924

TABLE III. RATIO OF "DIFFICULT" TO "EASY" IN TEXT-BASED LANGUAGE 1

ID	β_l/α_l	β_h/α_h	β_l/α_h	β_h/α_l	β_{l+h}/α_{l+h}
ma002	1.938*	0.895	1.049	1.558	1.264*
ma005	0.519*	1.382	1.020	0.693	1.153
ma006	1.740	0.859	1.171	1.171	1.046
ma007	0.850	1.029	0.992	1.074	1.026
ma011	1.264	1.592*	1.092	1.945*	1.466*
ma013	1.272	1.560*	1.195	2.119*	1.505*
ma015	0.805	1.119	1.153	0.892	1.021
ma021	1.150	1.361*	1.120	1.344	1.224*
ma024	1.468	1.637	1.611	1.384	1.108
ma026	0.971	1.113	1.072	0.983	1.053

TABLE IV. RATIO OF "DIFFICULT" TO "EASY" IN TEXT-BASED LANGUAGE 2

ID	β_l/α_l	β_h/α_h	β_l/α_h	β_h/α_l	β_{l+h}/α_{l+h}
ma001	0.972	0.885	0.600	1.292	0.961
ma003	0.683	1.072	0.875	1.025	0.969
ma004	0.916	1.769*	1.113	1.468	1.354*
ma007	1.293	1.067	1.217	1.154	1.320*
ma009	1.111	1.051	0.922	1.077	0.966
ma014	1.146	1.394*	1.199	1.214	1.225*
ma016	0.830	0.965	0.836	0.927	0.916
ma022	1.115	1.164	1.194*	1.195	1.233*
ma023	1.653*	1.403*	1.106	1.990*	1.302*

V. CONSIDERATION

Comparing the experimental result of the visual-type language (Table II), with the experimental results of the text-type language (Tables III and IV) showed that the visual-type language had less gray shading, whereas the text-type had many gray shades. This implied that when learning a text-type language, the values of various β/a were higher when solving difficult tasks, but this was not the case with the visual-type language.

The difficulty level of the visual-type language task may have been set inappropriately, but it is also likely that the visual- and text-type language use the brain differently, or think in different ways.

VI. CONCLUSION

We conducted experiments to solve tasks with various difficulty levels for learning visual-type and text-type languages, and measured the brain waves concurrently. By analyzing the β/a value indicating the difficulty level of the tasks according to the experiments, it was confirmed that the β/a value increases with the difficulty level for the text-type language. However, the β/a values for visual-type language experiments did not increase with the difficulty level. This suggests that in the learning process of visual-type language and text-type language, different thinking processes were performed.

In the future, we will conduct more extensive and rigorous experiments to further our study. In addition, educational content (intermediate language) that bridges the gap between the two language types will be developed. Finally, we aim to minimize the proportion of students who are frustrated in learning text-type languages, improve learning efficiency, and enhance comprehension.

ABOUT 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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APPENDIX

A. Experimental result

1) Average value of brain waves during the experiment

Tables V to X show the average values of various β/α (β_V/α_V , β_H/α_H , β_V/α_H , β_H/α_V , β_{V+H}/α_{V+H}) when solving problems with different difficulty levels for visual and text languages.

TABLE V. AVERAGE OF B/A WHEN SOLVING AN EASY QUESTION IN VISUAL LANGUAGE

ID	β_V/α_V	β_H/α_H	β_V/α_H	β_H/α_V	β_{V+H}/α_{V+H}
ma002	1.181	1.117	1.218	1.082	0.835
ma004	1.546	3.623	1.576	3.290	1.863
ma006	1.351	2.179	1.410	1.982	1.224
ma008	1.825	2.242	1.569	2.482	1.436
ma011	1.322	1.694	1.283	1.952	1.167
ma013	1.411	1.319	1.189	1.398	0.971
ma016	1.611	1.404	1.455	1.687	1.100

TABLE VI. AVERAGE OF B/A WHEN SOLVING A DIFFICULT QUESTION IN VISUAL LANGUAGE

ID	β_V/α_V	β_H/α_H	β_V/α_H	β_H/α_V	β_{V+H}/α_{V+H}
ma002	1.242	1.163	1.302	1.126	0.874
ma004	1.258	3.794	1.587	2.887	1.819
ma006	1.259	1.610	1.437	1.504	1.113
ma008	1.500	1.985	1.594	1.746	1.249
ma011	1.127	1.306	1.260	1.271	0.939
ma013	1.174	1.154	1.286	0.966	0.854
ma016	1.386	1.325	1.486	1.334	1.016

TABLE VII. AVERAGE OF B/A WHEN SOLVING AN EASY QUESTION 1 IN TEXT-BASED LANGUAGE

ID	β_V/α_1	β_H/α_h	β_V/α_h	β_H/α_1	β_{V+H}/α_{1+h}
ma002	1.078	1.243	1.300	1.062	0.881
ma005	1.406	1.738	1.096	2.346	0.993
ma006	1.169	2.389	1.185	2.420	1.328
ma007	1.307	1.346	1.449	1.015	0.915
ma011	1.057	1.484	1.222	1.065	0.922
ma013	0.989	1.083	1.146	0.856	0.748
ma015	1.536	1.347	1.347	1.147	0.952
ma021	1.130	0.994	1.301	0.939	0.824
ma024	0.887	0.923	0.988	0.896	0.724
ma026	1.233	1.326	1.226	1.408	0.953

TABLE VIII. AVERAGE OF B/A WHEN SOLVING A DIFFICULT QUESTION 1 IN TEXT-BASED LANGUAGE

ID	β_V/α_1	β_H/α_h	β_V/α_h	β_H/α_1	β_{V+H}/α_{1+h}
ma002	2.089	1.113	1.363	1.655	1.113
ma005	0.730	2.401	1.118	1.626	1.144
ma006	2.034	2.053	1.387	2.835	1.390
ma007	1.111	1.386	1.437	1.091	0.939
ma011	1.336	2.362	1.335	2.070	1.352
ma013	1.258	1.689	1.369	1.814	1.125
ma015	1.237	1.507	1.553	1.024	0.971
ma021	1.299	1.353	1.457	1.262	1.008
ma024	1.302	1.510	1.593	1.241	0.803
ma026	1.198	1.476	1.314	1.383	1.003

TABLE IX. AVERAGE OF B/A WHEN SOLVING AN EASY QUESTION 2 IN TEXT-BASED LANGUAGE

ID	β_V/α_1	β_H/α_h	β_V/α_h	β_H/α_1	β_{V+H}/α_{1+h}
ma001	1.509	1.688	2.126	1.258	1.169
ma003	1.521	1.285	1.364	1.111	0.900
ma004	1.279	1.600	1.295	1.443	0.970
ma007	0.950	1.240	1.134	1.008	0.738
ma009	1.683	0.943	1.620	1.089	0.939
ma014	1.192	1.326	1.137	1.259	0.909
ma016	2.164	1.290	1.677	1.818	1.157
ma022	1.108	1.248	0.957	1.158	0.770
ma023	0.766	1.522	1.101	1.083	0.894

TABLE X. AVERAGE OF B/A WHEN SOLVING A DIFFICULT QUESTION 2 IN TEXT-BASED LANGUAGE

ID	β_V/α_1	β_H/α_h	β_V/α_h	β_H/α_1	β_{V+H}/α_{1+h}
ma001	1.467	1.495	1.276	1.626	1.124
ma003	1.039	1.377	1.194	1.139	0.872
ma004	1.171	2.831	1.441	2.120	1.313
ma007	1.228	1.323	1.380	1.164	0.974
ma009	1.869	0.991	1.494	1.174	0.907
ma014	1.366	1.848	1.363	1.529	1.113
ma016	1.795	1.245	1.401	1.686	1.060
ma022	1.236	1.453	1.143	1.384	0.949
ma023	1.266	2.135	1.218	2.155	1.165

2) *t*-test result

Table XI shows the results (p -values) of the *t*-test (test of the difference between the average values) on the raw data before averaging in Tables V and VI. Similarly, the results of the *t*-tests in Tables VII and VIII are shown in Table XII, and the results of the *t*-tests in Tables IX and X are shown in Table XIII. The * mark in the table indicates that it became significant at the significance level of 5%, that is, it was judged that there was a difference in the average value.

TABLE XI. T-TEST RESULT (P -VALUE) IN VISUAL LANGUAGE

ID	β_V/α_1	β_H/α_h	β_V/α_h	β_H/α_1	β_{V+H}/α_{1+h}
ma002	0.634883	0.545313	0.322132	0.705520	0.339147
ma004	0.125522	0.611459	0.931893	0.227844	0.724510
ma006	0.598656	0.001288*	0.818535	0.038909*	0.121765
ma008	0.092467	0.156451	0.813730	0.013392*	0.005916*
ma011	0.096757	0.000440*	0.817327	0.015376*	0.000055*
ma013	0.440751	0.175280	0.421831	0.031084*	0.109491
ma016	0.185285	0.470217	0.802335	0.104487	0.121738

TABLE XII. T-TEST RESULT (P -VALUE) IN TEXT-BASED LANGUAGE 1

ID	β_V/α_1	β_H/α_h	β_V/α_h	β_H/α_1	β_{V+H}/α_{1+h}
ma002	0.005392*	0.458485	0.784792	0.059061	0.038411*
ma005	0.023048*	0.184138	0.923266	0.373443	0.365842
ma006	0.105114	0.339583	0.199367	0.568820	0.728297
ma007	0.361896	0.817342	0.946617	0.579817	0.730354
ma011	0.177854	0.001264*	0.355504	0.000023*	0.000057*
ma013	0.260772	0.011038*	0.255414	0.006023*	0.003613*
ma015	0.457094	0.545623	0.346812	0.529667	0.848399
ma021	0.521512	0.021955*	0.374611	0.120032	0.034931*
ma024	0.212846	0.127854	0.058032	0.470085	0.380936
ma026	0.849875	0.399918	0.558195	0.929348	0.581759

TABLE XIII. T-TEST RESULT (P -VALUE) IN TEXT-BASED LANGUAGE 2

ID	β_V/α_1	β_H/α_h	β_V/α_h	β_H/α_1	β_{V+H}/α_{1+h}
ma001	0.896547	0.623422	0.151539	0.176466	0.755684
ma003	0.222387	0.669967	0.328523	0.892585	0.767879
ma004	0.757246	0.000218*	0.519064	0.053904	0.001915*
ma007	0.084254	0.829427	0.418251	0.369240	0.001495*
ma009	0.569347	0.711265	0.687064	0.650284	0.703209
ma014	0.591098	0.000428*	0.080738	0.180132	0.010632*
ma016	0.329402	0.751488	0.177898	0.707091	0.279207
ma022	0.741026	0.217580	0.044875*	0.453410	0.004701*
ma023	0.002532*	0.000871*	0.314160	0.000007*	0.001484*