A Study on the Relationship Between Brain Waves, Heart Rate, and Facial Expressions During Programming Learning

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***Abstract*—Recently, there have been several on-demand learning systems that are not restricted by learning time or place. However, in these systems, learning content is prepared in advance for each learning course, or learning content of different difficulty levels is prepared, and learners select their learning contents. In contrast to these conventional systems, many studies have been conducted on learning systems that can grasp the learning state of individual learners and provide them with most suitable learning content. We experimentally verified a method for estimating the difficulty level of a task by focusing on alpha and beta waves. However, in practice, it is not feasible to have learners wear an electroencephalograph (EEG). This study aims to discover biometric information that can be measured by a nonwearable device as an alternative to EEG for estimating the learning state.**

***Index Terms*—programming learning, brain wave, heart rate, facial expressions**

I. Introduction

Recently, several full-online universities that adapt to a wide variety of lifestyles have appeared. As a new form of learning after COVID-19, online and hybrid lessons became necessary and spread rapidly. Furthermore, flipped classrooms have attracted significant attention as a methodology to increase student independence even in ordinary universities, and self-study conducted prior to face-to-face lessons plays an essential role. In this way, the demand for self-study increases. However, the conventional self-study system only uses the learning contents prepared in advance, and it is not possible to respond according to the learning state of each learner. We can do the same thing as a face-to-face class using video chat. However, the teacher's restraint time becomes too long to talk in real-time with the learner who wants to learn at any time.

We are promoting a research project on a self-study system that can grasp the learning state of each learner and provide the optimum learning content to the learner in such an on-demand type lesson that does not assume the guidance of a real-time teacher. In such project, we have been working on research to grasp the learning state using biological information, such as brain waves to grasp the learning state [1] [2]. In a series of these studies, we focused on α and β waves and experimentally verified a method for learners to estimate the difficulty of a task.

As a remaining issue of these studies, it was pointed out that it is not realistic for learners to wear an electroencephalograph (EEG) for learning to actually popularize this system. It was one of the remaining issues to estimate the learning state by another non-wearable biometric device that produces the same result as the estimation of the learning state through EEG.

This study aims to discover biometric information that is an alternative to brain waves to estimate the learning state and to explain the brain waves with such biometric information.

II. Previous work

A. Study on brain waves

It has been empirically found by studies in psychology and neuroscience that brain waves can be used as an index of a person's state of mind [3]. In previous studies, the α and β waves (obtained by analyzing the EEG power spectra in frequency space) were used to estimate a person's state of mind [4].

B. Applicability of brain waves to learning

The relationship between intellectual work and brain waves has been studied under the assumption that the β wave is strongly related to a person's mental state. For example, Giannitrapani investigated the relationship between intellectual work and brain waves by measuring the brain waves of a person taking an intelligence test [5]. The low frequency component of the β wave was dominant during the reading and comprehension, mathematics, and diagram tests.

C. Estimating task difficulty using an EEG

Other researchers have found that the power spectra of the α and β waves, the ratio of the α and β waves in relation to all brain waves, and the simple ratio of the α and β waves are effective in estimating a person's state of mind [6]. It was also shown that the activity of a person's brain could be estimated by measuring the α and β waves and estimating β/α [7]. In a previous experiment using a simple typing test with varying degrees of difficulty, we confirmed that the β/α ratio increases with task difficulty [8]. We also found that the low-β-wave/low-α-wave ratio, where "low" means low frequency, increases as a person works on a difficult task [9]. Another experiment was conducted where the change in brain waves was measured as the examinees became used to a new task (assembling a robot using three-dimensional motion capture). In this experiment, we showed that, although the examinees became accustomed to the task in various ways, the low-β/low-α ratio of the examinees who reported that the task was easy fell gradually [10]. We proposed a system and a method for estimating the learning state of the learners by comprehensively analyzing his/her learning history and brain wave. We also evaluated the learning state of high school students learning the C and Scratch programming languages using the proposed method. Additionally, we evaluated the effectiveness of the proposed method by comparing the estimated results with those obtained from the questionnaire administered after the experiments [11].

III. Proposal

We measured multiple types of biometric information (brain waves, HR, and facial expressions) simultaneously when performing programming tasks (easy, medium, and difficult tasks) with different difficulty levels. We also analyzed the obtained data and tried to explain the brain waves with biological information other than the brain waves, such as HR and facial expressions.

IV. Experimental method

A. Questions to use for the experiment

For the question used in this experiment, we used a website called Paiza learning [12], where we can learn programming on the Web. This site offers a wide range of questions for beginners to experts. It also has a function to judge how many people challenge each question and what percentage of correct answers are. Correctness is judged in ten test cases, and the score is determined by measuring the correct answer rate, execution speed, and memory consumption. It is evaluated by the correct output (out of 50 points) and the speed to answer (out of 50 points) in multiple test cases. We used this site because the question that the experimenter solved is automatically judged, and the difficulty level of the question can be judged. The difficulty level was set to three levels when selecting the question to be used in this experiment. Therefore, we selected the questions to be used in the experiment by referring to the number of participants and the percentage of correct answers for the questions on this site. In this experiment, from the skill check of Paiza learning, we used the questions with correct answer rates of 91.88%, 80.84%, and 49.35% as of December 20, 2021. We used the Java programming language for the experiments. The question used in this experiment is shown in Figures 1, 2, 3 with a brief outline because it is impossible to put the photo or text as it is due to the handling rules of Paiza learning.

D rank question 114: Price including tax

The input is two numbers. The first number is the consumption tax rate (%), and the second number is the tax-excluded price. Output the tax-included price using these two inputs. The result is rounded down to the nearest whole number.

Fig. 1. Summary of Question A

C rank question 017: High and low card game

Two data are input in the first line. One numerical value N is input into the second line. Two data for N times are input after the third line. The first line is the parent, and the third and subsequent lines are the children. A strong-weak relationship is shown by comparing parents and children according to a certain law. If the parent card is strong, it will be displayed as "High;" otherwise, it will be displayed as "Low."

Fig. 2. Summary of Question B

B rank question 016: Where is here?

Three numbers are input in the first line. The three numbers are the width and height of the map and the movement log. Two numbers are input in the second line. These two numbers represent the X and Y coordinates on the map. From the third line onward, letters and numbers are input. The letters indicate the direction where the character moves, and the numbers indicate the distance traveled. When the character moves to the edge of the map, if it tries to go further in that direction, it moves to the opposite coordinates and moves the remaining distance.

Fig. 3. Summary of Question C

B. Biological equipment used for experiments

1) Simple EEG: MindWave Mobile 2 from NeuroSky is used for EEG measurement. As presented in [13], this headset can detect potential differences (voltage) between the forehead (FP1 position of the international 10–20 system for EEG) and the ear (A1 position). The signals are passed through low- and high-pass filters to retain signals in the range of 1–50 Hz. The headset was used to perform aliasing correction, 128 Hz sampling, noise artifact detection, correction, and frequency component transform (fast Fourier transform (FFT)). EEG data are collected from the log collection application on the PC. The log collection application communicates TCP/IP with the ThinkGear Connector, and the ThinkGear Connector connects the headset via Bluetooth to collect logs. ThinkGear Connector is a driver provided by NeuroSky that has a communication function with MindWave Mobile 2. Additionally, the types of electroencephalograms that can be acquired by this simple EEG are the eight types shown in Table I. Each value is a 4-byte floating fractional value without a unit.

In this paper, we used four types of low α wave, high α wave, low β wave, and high β wave according to the previous study [7]. After that, the low α wave is referred to as α_l; the high α wave is referred to as α_h; the low β wave is referred to as β_l; the high β wave is referred to as β_h. According to the previous work [10], we use five kinds of β/α values by adding the average of low and high frequencies $(\beta_l + \beta_h)/(\alpha_l + \alpha_h)$ to four kinds of β/α combinations $(\beta_l/\alpha_l, \beta_h/\alpha_l, \beta_l/\alpha_h, \beta_h/\alpha_h)$. Hereafter, $(\beta_l + \beta_h)/(\alpha_l + \alpha_h)$ is referred to as β_{l+h}/α_{l+h}.

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

2) Heart rate (HR) monitor: The "myBeat" wearable HR sensor WHS-1 manufactured by Union Tool Co., Ltd. is used for HR measurement. WHS-1 can measure three types of biometric data: HR, acceleration, and body surface temperature. Measurement is possible using a dedicated USB receiver and the attached dedicated software. This time, HR is used among the measured values.

3) Facial expression: Facial expression recording and analysis are required to determine facial expressions. A Logicool C920n webcam is used to record facial expressions. A Kokoro sensor manufactured by CAC Corporation (equipped with the emotion recognition engine manufactured by Affectiva) that analyzes the captured image is used for facial expression analysis. This application can recognize human faces from captured or real-time images and quantify emotions (anger, contempt, disgust, fear, joy, sadness, surprise, neutral, engagement, and valence). Additionally, blinking, face orientation, and coordinates of facial parts can be quantified. This time, we use the above ten kinds of quantified emotions. In these emotions, except for the valence, they are expressed by a numerical value between 0 and 100, and the valence is expressed as a numerical value from -100 to 100. We consider anger, contempt, disgust, fear, sadness, and surprise as negative emotions and joy as positive emotions.

C. Experiment participants

The participants in the experiment were nine fourth-year students of Shonan Institute of Technology. They studied programming-related courses in the same department at the same university for four years. Their programming skills are comparable.

D. Experimental method

First, the participants in the experiment are asked to wear measuring devices (EEG and HR monitor) that measure biological information. A webcam that records facial expressions is installed on the PC monitor. The distance between the PC monitor and the participant is approximately 1 m, as in normal desktop PC work. First, as a test of the measuring device, the biometric information is measured for about 5 minutes when nothing is done (just sitting on a chair). Next, programming is performed in the order of Questions A, B, and C, and the biometric information at that time is measured. Each time was set to 10, 20, and 30 minutes for Questions A, B, and C, respectively . However, this set time was not notified to the participants in advance, and the experiment was conducted. We decided to put a break of about 1 minute between each question. The flow of the experiment is shown in Figure 4.

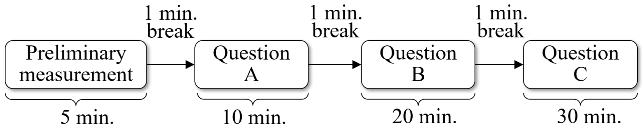

Fig. 4. Experimental flow

The experiments were conducted in a laboratory at the Shonan Institute of Technology. The experiments were conducted as quietly as possible. The experiment is shown in Figure 5.

Fig. 5. Conditions of an experiment

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Analysis of average value

The experimental results of participant 1 are shown in Table II. Each numerical value is the average value of biometric information measured while solving each question. Note that, for space reasons, only the data from one participant is presented here, but the analysis in the subsequent sections uses data from all nine participants.

In Table II, the experimental results of participant 1 are shown. Data for nine participants in the experiment could be obtained. In this study, we aim to determine biometric information that can replace brain waves (β/α). Therefore, the objective variables are individual brain waves β/α, and the explanatory variables are HR, anger, contempt, disgust,

TABLE II
AVERAGE VALUE OF BIOMETRIC INFORMATION OF EXPERIMENT PARTICIPANT 1

	Kind	Alias	A	B	C
Brain wave	β_l/α_l	y_1	0.5885	0.5592	0.6910
	β_h/α_l	y_2	0.4422	0.4619	1.0417
	β_l/α_h	y_3	0.8259	0.7951	0.9352
	β_h/α_h	y_4	0.7515	0.8260	1.5074
	β_{l+h}/α_{l+h}	y_5	0.6019	0.5995	0.9965
HR	heart rate	x_1	64.2138	62.3829	47.7976
Facial expression	anger	x_2	0.0601	0.0605	0.0838
	contempt	x_3	0.1910	0.1929	0.1942
	disgust	x_4	0.0201	0.0203	0.0716
	fear	x_5	0.0213	0.0213	0.0331
	joy	x_6	0.0816	0.0202	0.0210
	sadness	x_7	0.0599	0.0600	0.3486
	surprise	x_8	0.0216	0.0216	0.0387
	neutral	x_9	99.5420	99.6110	99.0507
	engagement	x_{10}	0.4217	0.3380	0.4203
	valence	x_{11}	0.0635	0.0094	0.0367

fear, joy, sadness, surprise, neutral, engagement, and valence. Multiple regression analyses were performed. If a significant partial regression coefficient can be obtained with this, it is possible to substitute brain waves with HR and facial expression.

As shown in Table III, only $\beta_l/\alpha_l(y_1)$ and $\beta_l/\alpha_h(y_3)$ had a coefficient of determination (contribution rate) of 0.5 or more.

TABLE III
COEFFICIENT OF DETERMINATION (CONTRIBUTION RATE) OF MULTIPLE REGRESSION EQUATIONS FOR OBJECTIVE VARIABLES (y_1 TO y_5)

Objective variables	Coefficient of determination R^2 (Contribution rate)
y_1	0.5591
y_2	0.3412
y_3	0.7063
y_4	0.2417
y_5	0.3758

Each multiple regression equation is as follows.

$$\begin{aligned}\hat{y}_1 = {} & -0.0002x_1 + 0.6322x_2 - 0.0470x_3 + 0.0226x_4 \\ & +0.0188x_5 + 0.0145x_6 + 0.0452x_7 - 0.2270x_8 \\ & +0.0323x_9 + 0.0025x_{10} + 0.0164x_{11} - 2.6525\end{aligned} \tag{1}$$

$$\begin{aligned}\hat{y}_3 = {} & +0.0015x_1 + 0.3682x_2 - 0.1483x_3 + 0.2411x_4 \\ & \mathbf{-2.8462}x_5 + 0.0077x_6 - 0.1272x_7 + 0.7492x_8 \\ & -0.0175x_9 - 0.0031x_{10} - 0.0193x_{11} + 2.5703\end{aligned} \tag{2}$$

However, among the regression coefficients of each variable in the above two equations, the only one whose p-value was significant at the 5% level was the coefficient -2.8462 of x_5 in the equation of y_3. This is because other explanatory variables cannot be considered as factors that change β/α.

B. Analysis of the difference

As shown in the previous section, it was not possible to obtain a valid multiple regression equation with the mean value of biometric information when solving each question. Therefore, we focus on the difference in the difficulty of the questions and the difference in the average value of the biometric information when solving each question.

The experimental results of participant 1 are shown in Table IV. Each numerical value is the difference between the average values of biometric information measured while solving each question. For example, AB is the difference between the average value of biometric information when solving Question B and the average value of biometric information when solving Question A.

TABLE IV
DIFFERENCE IN AVERAGE VALUE OF BIOMETRIC INFORMATION OF EXPERIMENT PARTICIPANT 1

	Kind	Alias	AB	AC	BC
Brain wave	β_l/α_l	w_1	-0.0293	0.1025	0.1318
	β_h/α_l	w_2	0.0197	0.5995	0.5798
	β_l/α_h	w_3	-0.0308	0.1093	0.1401
	β_h/α_h	w_4	0.0745	0.7560	0.6815
	β_{l+h}/α_{l+h}	w_5	-0.0024	0.3946	0.3970
HR	heart rate	z_1	-1.8310	-16.4162	-14.5853
Facial expression	anger	z_2	0.0004	0.0236	0.0233
	contempt	z_3	0.0019	0.0033	0.0014
	disgust	z_4	0.0003	0.0516	0.0513
	fear	z_5	0.0000	0.0118	0.0118
	joy	z_6	-0.0614	-0.0607	0.0008
	sadness	z_7	0.0001	0.2887	0.2886
	surprise	z_8	0.0000	0.0171	0.0171
	neutral	z_9	0.0689	-0.4914	-0.5603
	engagement	z_{10}	-0.0837	-0.0014	0.0823
	valence	z_{11}	-0.0541	-0.0267	0.0273

As in the previous section, the objective variables are individual brain waves β/α, and the explanatory variables are HR, anger, contempt, disgust, fear, joy, sadness, surprise, neutral, engagement, and valence. Multiple regression analyses were performed. Consequently, the coefficient of determination (contribution rate) was high for all objective variables (w_1 to w_5). Table V presents the coefficient of determination (contribution rate) of each multiple regression equation. As a general guideline, if the coefficient of determination (contribution rate) is 0.5 or 0.6 or more, it is considered that a useful regression equation was obtained. Therefore, it can be said that a useful regression equation was obtained for all the objective variables.

TABLE V
COEFFICIENT OF DETERMINATION (CONTRIBUTION RATE) OF MULTIPLE REGRESSION EQUATIONS FOR OBJECTIVE VARIABLES (w_1 TO w_5)

Objective variables	Coefficient of determination R^2 (Contribution rate)
w_1	0.8906
w_2	0.9186
w_3	0.8995
w_4	0.8575
w_5	0.9030

Each multiple regression equation is as follows. The regression coefficients shown in bold in the formula below indicate that the p-value was significant at the 5% level due to multiple regression analyses. It can be seen that many explanatory variables are significant at the 5% level. The actual p-value is presented in Table VI. As a residual analysis, we plotted the residuals on a graph. The residuals were evenly distributed around the vertical axis 0, and there seemed to be no outliers. The observed-predicted plot and the residual-predicted plot for five types of β/α is shown in appendix.

$$\begin{aligned}\hat{w}_1 \;=\; & \mathbf{-0.0074}z_1 + 0.1400z_2 \mathbf{+0.2357}z_3 \mathbf{-0.3210}z_4 \\ & \mathbf{+4.4347}z_5 \mathbf{+0.2137}z_6 + 0.1805z_7 \mathbf{-0.9765}z_8 \\ & \mathbf{+0.1322}z_9 \mathbf{-0.0164}z_{10} \mathbf{-0.0441}z_{11} - 0.0249\end{aligned} \tag{3}$$

$$\begin{aligned}\hat{w}_2 \;=\; & \mathbf{-0.0408}z_1 + \mathbf{2.2297}z_2 - 0.2697z_3 \mathbf{-0.5901}z_4 \\ & -1.0580z_5 - 0.3072z_6 \mathbf{-0.7093}z_7 \mathbf{-2.1025}z_8 \\ & -0.2420z_9 + 0.0049z_{10} + 0.0498z_{11} + 0.0237\end{aligned} \tag{4}$$

$$\begin{aligned}\hat{w}_3 \;=\; & \mathbf{-0.0117}z_1 + \mathbf{1.0896}z_2 - 0.0903z_3 + 0.1010z_4 \\ & \mathbf{-1.9064}z_5 + 0.0650z_6 - 0.2159z_7 - 0.2238z_8 \\ & -0.0080z_9 \mathbf{-0.0149}z_{10} \mathbf{-0.0453}z_{11} - 0.0015\end{aligned} \tag{5}$$

$$\begin{aligned}\hat{w}_4 \;=\; & \mathbf{-0.0545}z_1 \mathbf{+3.8361}z_2 \mathbf{-1.4383}z_3 - 0.5347z_4 \\ & \mathbf{-9.5242}z_5 \mathbf{-1.2274}z_6 \mathbf{-2.0989}z_7 \mathbf{-2.9426}z_8 \\ & \mathbf{-0.9611}z_9 \mathbf{+0.0366}z_{10} \mathbf{+0.1642}z_{11} + 0.0438\end{aligned} \tag{6}$$

$$\begin{aligned}\hat{w}_5 \;=\; & \mathbf{-0.0288}z_1 \mathbf{+1.8311}z_2 - 0.2136z_3 - 0.2655z_4 \\ & -1.6070z_5 - 0.1538z_6 \mathbf{-0.5218}z_7 \mathbf{-1.3650}z_8 \\ & -0.1501z_9 - 0.0042z_{10} + 0.0076z_{11} + 0.0131\end{aligned} \tag{7}$$

Considering these multiple regression equations, the HR (z_1) is significant in all equations, and all coefficients are negative. It can be said that the lower the HR, the larger the difference in brain waves (β/α). According to a previous study, it can be said that the difference in brain waves is the difference in difficulty (the degree to which the task is difficult), so if you go from simple questions to difficult questions, your HR will drop. Anger (z_2) is significant in many equations as well as HR, and all coefficients are positive. The more angry the expression, the greater the difference in brain waves (β/α). It can be seen that there is a positive correlation between increasing the expression of anger and increasing the difficulty level. This result is intuitive. Surprise (z_8) is also significant in many equations. It can also be said that the higher the surprise, the smaller the difference in brain waves (β/α). It can be thought of as a surprise because the task was too difficult or a reduction in brain waves (β/α) due to giving up.

VI. CONCLUSION AND FUTURE WORK

In this study, we measured biometric information (brain waves, HR, and facial expressions) when performing programming tasks of different difficulty levels. We performed an analysis using the multiple regression analysis methods with the measured data to find biometric information that can replace brain waves. A significant regression equation could not be obtained from the average value of biometric information when performing each task. However, we obtained a significant regression equation by focusing on the difference in the average values of biometric information when performing tasks of different difficulty levels. This makes it possible to estimate the value of brain wave (β/α) from the HR and facial expression. It is also possible to estimate the learning state without wearing an EEG during learning.

In future studies, we will measure the biological information of another experimental participant and verify whether the brain waves can be accurately estimated from the HR and facial expression using this regression equation. In addition, this time the analysis was conducted using a simple regression equation; in the future, we would like to use machine learning techniques to perform our analysis.

RESEARCH ETHICS

The experiments were approved by the Research Ethics Committee of Shonan Institute of Technology. We also received signatures from examinees and parents of the examinees concerning experiment participation.

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TABLE VI
p-VALUE OF REGRESSION COEFFICIENT

Obj. variable	heart rate z_1	anger z_2	contempt z_3	disgust z_4	fear z_5	joy z_6	sadness z_7	surprise z_8	neutral z_9	engage-ment z_{10}	valence z_{11}	inter-cept
w_1	0.0007*	0.6153	0.0027*	0.0012*	0.0000*	0.0047*	0.1077	0.0027*	0.0247*	0.0000*	0.0022*	0.0531
w_2	0.0000*	0.0036*	0.1044	0.0076*	0.4905	0.0633	0.0126*	0.0053*	0.0734	0.4749	0.1004	0.4132
w_3	0.0002*	0.0103*	0.3292	0.3729	0.0424*	0.4715	0.1539	0.5550	0.9135	0.0014*	0.0142*	0.9295
w_4	0.0000*	0.0084*	0.0003*	0.1735	0.0053*	0.0009*	0.0006*	0.0339*	0.0014*	0.0129*	0.0098*	0.4381
w_5	0.0000*	0.0025*	0.0999	0.0962	0.1893	0.2179	0.0175*	0.0162*	0.1470	0.4287	0.7369	0.5613

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APPENDIX

A. Observed-predicted plot and the residual-predicted plot

Figures 6 to 10 show the observed-predicted plot and the residual-predicted plot of five types of β/α. Looking at the residuals-predicted plot, the residuals are evenly distributed around the vertical axis 0, and there seems to be no outliers.

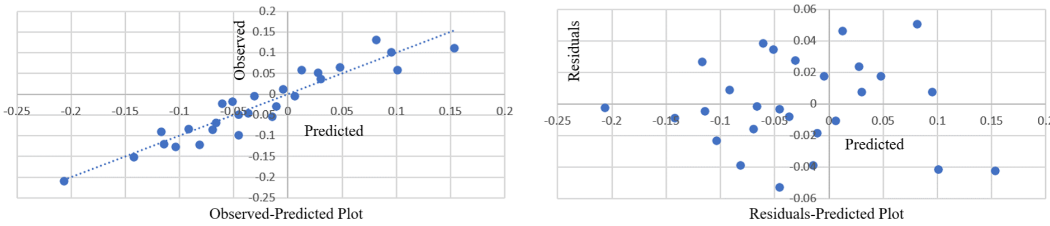

Fig. 6. Observed-predicted plot and the residual-predicted plot of β_l/α_l

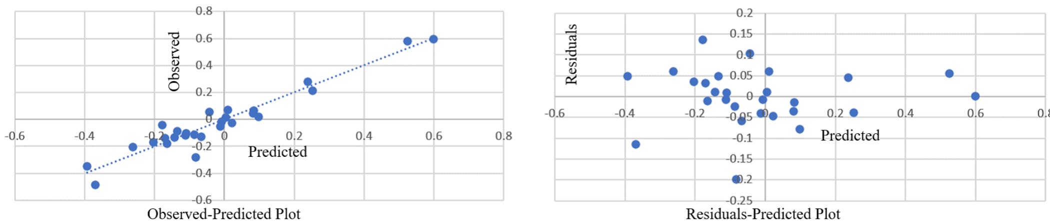

Fig. 7. Observed-predicted plot and the residual-predicted plot of β_h/α_l

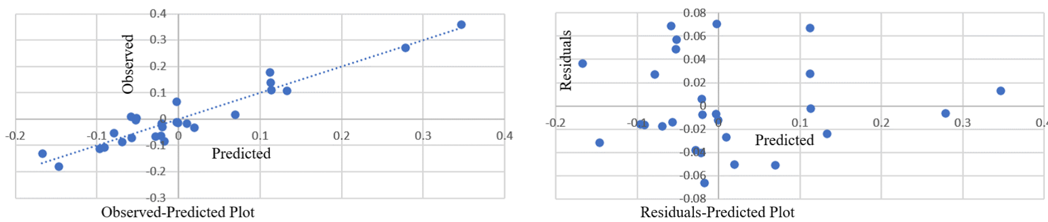

Fig. 8. Observed-predicted plot and the residual-predicted plot of β_l/α_h

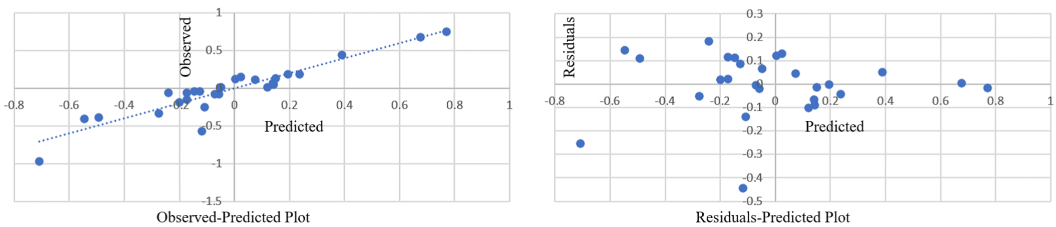

Fig. 9. Observed-predicted plot and the residual-predicted plot of β_h/α_h

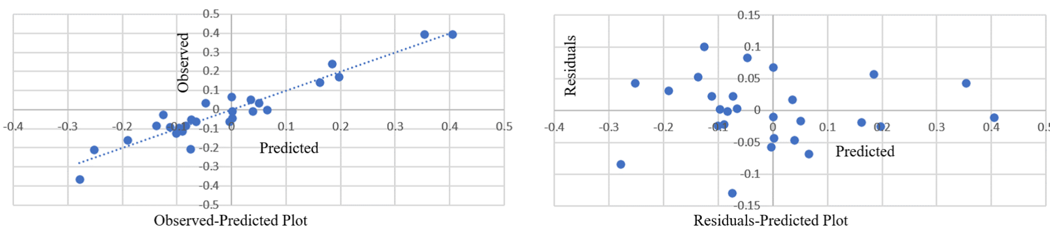

Fig. 10. Observed-predicted plot and the residual-predicted plot of β_{l+h}/α_{l+h}