Programmer's Electroencephalogram who found Implementation Strategy

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***Abstract*— Electroencephalogram (EEG) is one of the useful tools to measure programmer's state for effective support in proper moment. The purpose of this study is to investigate effectiveness of EEG as an index for classification of programmers who fail to find an implementation strategy. We select three major metrics for EEG measurement; alpha wave, beta wave, and their ratio. Then we experimentally analyze the differences between two conditions; 1) find a strategy, and 2) do not. The result of the experiment shows that the power of alpha wave and alpha-beta ratio are increased when participants found the implementation strategy.**

Keywords—EEG; Biomedical Measurement; implementation strategy;

I. INTRODUCTION

Providing proper and prompt support to software developers is a key for their effective work. Students who learns programming also needs such support to optimize their learning efficiency. However, it is hard to classify whether a developer presently needs support; Because programming activity (or other intellectual work) has little visible characteristics that indicates developer's inner condition. Even if a developer is stuck with his/her task, their supervisor can hardly classify developer's current situation without any intervention. Additionally such intervention may disturb developer's concentration. This situation needs methods to classify developer's present condition without any intervention to keep their concentration level high.

In this paper, authors propose a method to classify states of developers without any interruption. To achieve the goal, we employ a brain wave measured with Electroencephalogram (EEG). EEG allows non-invasive observation of electrical processes in the cerebral cortex, which tends to reflect our individual thoughts, emotions and behavior [1]. Because of less restriction and low device cost, EEG has been used in many research domains [2][3]. In software engineering domain, several studies have employed EEG to measure brain activity during programming [1][4]. Among frequency components of EEG, alpha and beta waves are well-used indexes of relaxation and mental condition [5].

Authors hypothesize that developer's mental events, such as success to find a proper implementation strategy or algorithm, affect his/her psychological state. Here, implementation strategy means a set of algorithm, template or well-known code snippet to realize required functions. We hypothesize that developer who found an appropriate implementation strategy have a measurable differences in their brain wave compared with who fail.

In an experiment, we measured a brain wave during program tasks and compare its frequency components between the participants who success to find an implementation strategy and others who fail. We recorded a brain wave in two different time periods, during task and after task. Alpha wave has a characteristic that becomes a stronger when the participants close their eyes. Therefore, EEG is usually recorded at eye-closed condition to reduce the effect from noise. However, participants need to open their eyes to read the code during the programming task. We compare two EEGs in the experiment, 1) EEG recorded during the task with open-eyes, and 2) EEG recorded after the task with closed-eyes.

II. RELATED WORD

Several studies have measured developer's brain activity as an index of their workload and mental processes [6][7]. Brain activity measurement allows us to directly observe what is happening inside developer's brain during programming task such as implementation or program comprehension. The research results are essential clue to understand the difference between good programmer and bad programmer, or how to build effective developer supports.

Siegmund et al. have measured brain activity during program comprehension by fMRI, one of the equipments to measure brain activity [6]. The result has shown that brain regions that related to problem solving, memory and sentence understanding were activated during program comprehension task. Nakagawa et al. have compared the brain activity at different difficulty of program understanding task [7]. The result has shown that cerebral blood flow at prefrontal regions increased from early to middle stage of the task. Müller et al. have investigated the relationship between developer's emotion and biometrical indicators including a brain wave [8][9]. In their experiment, a classifier based on a biometric data succeeded in predicting 71.36% of all cases. Their result indicates sensing a brain wave can provide rich information of developer's emotional states.

In this paper, we use EEG to measure programmer's brain activity on programming task. Other brain activity measurement devices such as fMRI and NIRS strictly require immovable state for participants to accurate measurement. Such restriction may cause an unusual brain activity during programming task. EEG is a device that have a smaller restriction to participant's movement compared with fMRI and NIRS. Hence, EEG is more appropriate measurement method in practical programming environment. Also most of EEG device are inexpensive than other devices. Therefore, establishment of analysis method using EEG to classify programmers who fail to find the implementation strategy is useful for future implementation.

III. EEG

A brain wave is an electrical activity that arises from brain and recorded through electrodes placed on the scalp [10]. Brain electric potential is measured as difference of two electrodes potential. Each electrode is placed on point that specified by the International 10-20 system shown in Figure 1. The 10-20 system designates 19 electrode placements except the electrodes defining ground potential.

The purpose of measurement defines number of electrodes. There are two electroencephalographic derivation methods; standard and bipolar method. The standard method is used when two electrodes are placed near to each other. The bipolar method is used to measure difference of two specific positions and remove the irrelevant background components.

EEG analysis is typically based on frequency components from single task. International Electroencephalographic Society defines following bandwidths [10].

- Delta wave: 1Hz-3Hz
- Theta wave: 4Hz-7Hz
- Alpha wave: 8Hz-13Hz
- Beta wave: 14Hz-30Hz

These indexes are used as metrics of human psychological condition in various works [4]. For example, alpha wave appears strongly when a subject is in relaxation or under concentration. When a subject is in stressful state or thinking, beta wave becomes stronger and alpha wave becomes relatively weakened.

We hypothesize that developer who succeeded to find an implementation strategy shows strong beta wave and relatively weak alpha wave. On the other hand, developer who is struggling to find an implementation strategy feels a lot of stress. We hypothesized that their alpha wave is reduced and beta wave increases.

EEG analysis generally uses Fast Fourier Transform (FFT) to obtain power spectrum. The procedure to obtain the power spectrum is as follow:

1) Data acquisition
   Extract N^2 continuous values from the measured EEG.
2) Remove trend
3) Remove a trend (unnecessary frequency component) by a filter.

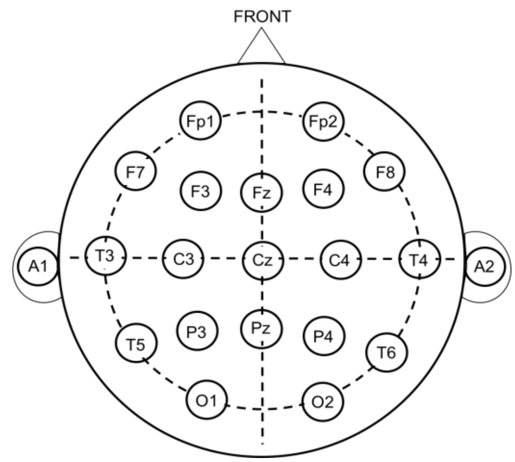

Fig.1. Electrode placement at International 10-20 system

4) Data window
   Take a window function to smoother both ends of the section.
5) Calculation of FFT
   The power spectrum obtains by the following calculation formula; here, *t* is time, *x* is measured EEG raw data, *g(x)* is all real numbers.

$$f(t) = \int_{-\infty}^{\infty} g(x)\left(\cos(2\pi xt) + j\sin(2\pi xt)\right)dx$$

IV. EXPERIMENT

We measured participant's brain wave with EEG during programming task. Participants were 17 students of National Institute of Technology, Nara College, their age ranged from 16 to 20. All participants have finished a basic lecture of programming.

A. Environment

Experiment is carried out in a quiet room that has two experimenters and one participant. We use NeXus-10 MARK II made in Mind Media Inc. as EEG measurement device. Figure 2 shows the appearance and measurement state. The device measures a brain wave with 256Hz sampling frequency, and a measured data is transferred to PC via Bluetooth. We use one PC for device control, data recording, and source code display. The display size and resolution are 21.3-inch, 1920 x 1200 [ppi]. We have participants sit on a chair with headrest and elbow rest, then adjust the seat height comfortable condition to minimize noise caused from body movement. Experimenters operate all experiment devices, participant operates nothing.

B. EEG Measurement

We attach EEG device to a participant and measure a brain wave. Electrodes are located using the standard electrode derivation method. Ground electrode is located at right ear (A2), standard electrode is located at left ear (A1) and measurement electrode is located at back of the head (Pz).

EEG is usually recorded at eye-closed condition to reduce the effect from eye-blinking noise. However, participants who at task open their eyes to read the source code that displayed on PC screen, hence the blink will make some myoelectric potential around the eyes. In our experiment, two different time periods is used to measure EEG; during task (task state) and after the task (rest state.) Ohashi et al. have reported that an effect from experiment task remain to EEG during 60 to 100 seconds after the task [3]. It means the EEG which recorded after the task with closed-eyes contains the task effects without any artifacts from body movement during the task. On the other hand, EEG recording after the task requires additional measurement time; i.e. causes longer restriction of subjects, or slow classification of developer condition in practical programming environment. In this paper, we compare two EEGs 1) EEG recorded during task, and 2) EEG recorded after task for understanding of appropriate recording method for programming task.

C. Task

Participants are asked to find an implementation strategy for the question within 60 seconds. Participants answer solution verbally after each task. In each task, participants fill in blank based on simple explanation written in natural language. Source codes are 10 to 30 lines Java program consisting of one class and one to three methods. We prepare twelve questions as the task; for example, sorting, Caesar cipher and eight queens puzzle. Difficulties are widened to observe both the states; success to find implementation strategy, and fail. The order of question is counter balanced to avoid an order effect. Figure 3 is a screen display for task screen. The experiment procedure is shown below.

1) Experiment explanation and preparations
   Explain about the experiment and EEG measurement.
2) Device setting
3) Attach electrodes and set EEG measurement device to a participant.
4) Measurement during task

[a]NeXus-10 MARK II [b]Measurement example

Fig. 2. Measurement environment

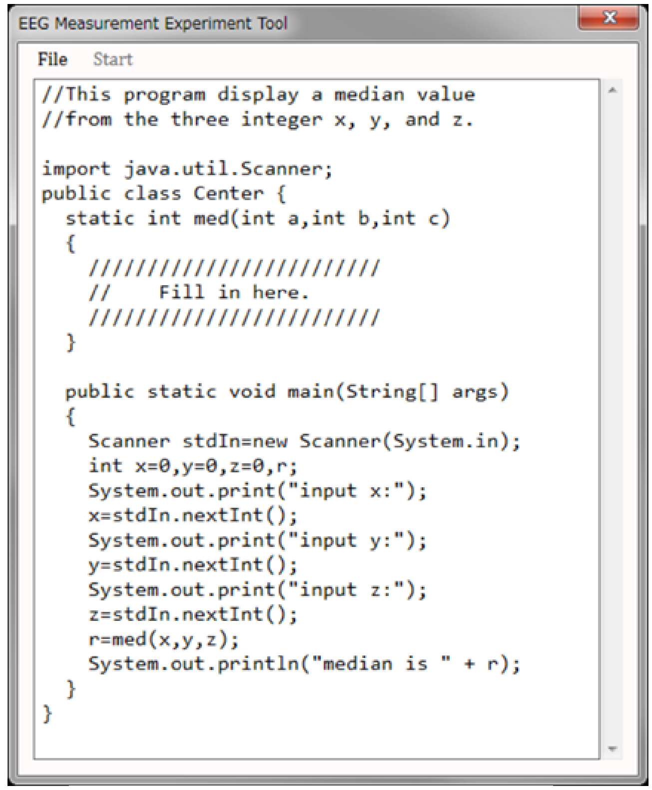

Fig.3. EEG measurement experiment tool

   Participants think implementation strategy of task for 60 seconds. At the same time we measure EEG.
5) Oral answer
   Participants explain strategy verbally. The correctness of the strategy is ignored;
6) Measurement after task
   Participants maintains closed eyes at resting state for 120 seconds. At the same time we measure EEG.
7) Execution of all tasks
   Repeat procedure from 3) to 5) in twelve times.

D. Analysis

After applying filters to EEG data, we obtain power spectrum with FFT. Frequency components of alpha and beta wave were extracted as power spectrum. Extracted component is normalized with the mean of each participant's component to minimize an effect from individual differences of EEG. In this experiment, we select three metrics for analysis:

- Normalized power of alpha wave (alpha)
- Normalized power of beta wave (beta)
- Ratio of beta and alpha wave (beta/alpha)

We classify the each task as “success to find an implementation strategy” (*success* group) and “fail to find within given time” (*fail* group), then compare three metrics between these groups. At first, we apply F-test of the equality of two variances for each metric. When the metric has a

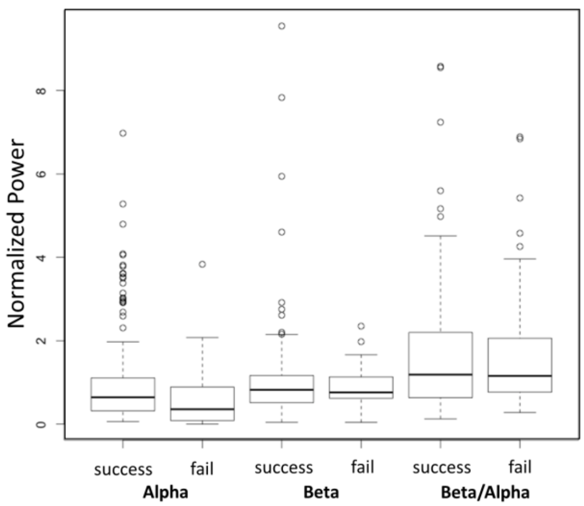

Fig. 4. EEG during task

homoscedasticity, we examine significant difference between groups with t-test, otherwise with Welch's t-test.

V. RESULT AND DISCUSSION

A. *EEG During Task*

Figure 4 shows two group's alpha, beta, and beta/alpha waves during task. The result shows alpha and beta/alpha of the *success* group is higher than *fail* group. The result of t-test shows that difference of alpha (p=0.049) and beta/alpha (p=0.035) are significant. Beta (p=0.406) shows no significant differences.

The result suggests that power of alpha wave and beta/alpha ratio during task are useful metrics to classify programmers who find an implementation strategy. On the other hand, beta wave is affected from various thinking or mind condition, such as stress from unusual environment, i.e. experiment room and EEG measurement device on his/her head. As described in Section 3, beta wave appears when participants under stress or unpleasant feelings. Confirmation of the beta wave during programming task is a one of the future works.

Another possible effect for EEG measurement is an artifact from eye blinking. Participants during task open their eyes to read the source code displayed on PC screen, hence the blink will make some myoelectric potential around the eyes. However the effect might be small since it was measured at occipital (back side of the head) in this experiment. Therefore, EEG during task is useful index to classify developer succeeded or failed to find an implementation strategy.

B. *EEG After Task*

Figure 5 shows two group's alpha, beta, and beta/alpha waves recorded after task. The figure shows a similar tendency with metrics recorded during task; alpha and beta/alpha of *success* group is higher than *fail* group. The

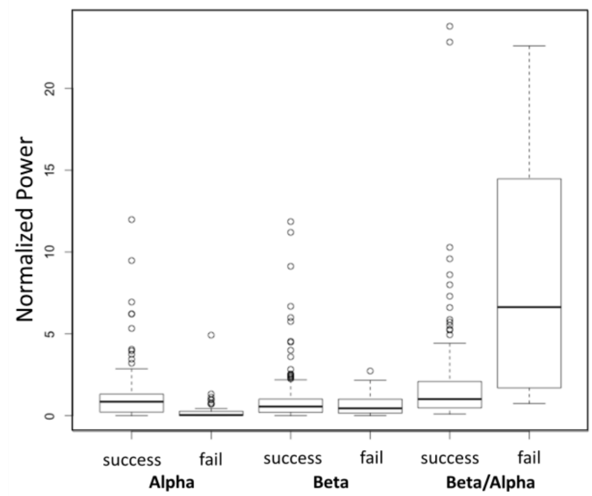

Fig. 5. EEG after task

result of t-test shows that the difference between two groups of alpha (p=0.003) is significant. Beta (p=0.147) and beta/alpha (p=0.343) have no significant difference.

The result suggests that the power of alpha wave after the programming task is a useful metrics to classify programmers who find an implementation strategy. The power of alpha wave after tasks is larger than that recorded during task, so the signal/noise ratio is better. Beta wave and beta/alpha have no significant differences at the EEG after the task. Similar to the EEG during the task, beta wave might be affected by the stress from the experiment settings.

C. *Components of Each Individual*

Two results from Figure 4 and Figure 5 shows many outliers exist in all metrics at both EEG. One of the possible reasons is the individual differences. Figure 6 shows the alpha value of each participant after the task in the *success* group. The horizontal axis shows the participant ID, the vertical axis represents the logarithmic axis of alpha wave after normalization. The figure shows one of the participants (No.10) has an extremely small value compared with other participants. Since the values are normalized by the average value of each participant, the result means that the participant has a larger value when he fails to find the implementation strategy. Some studies about brain measurement reported in case of some participants have extremely different value and/or the opposite tendency [7]. The results of our experiment may also contain the effect of such individual difference.

Table 1 presents the component values of each participant. Each component value is the median, and p describes the p-value of t-test. The asterisk (*) marks the p-value is less than 0.05. In the table, nine participants (52.9% of all participants) have a significantly larger alpha at *success* (i.e. they found the implementation strategy) than *fail*. Also nine participants (52.9%) have a significantly smaller beta/alpha ratio at

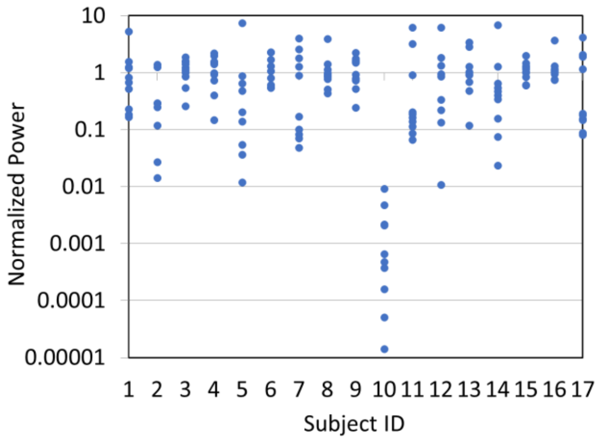

Fig. 6. Alpha waves of each subject in *success* group

success than *fail*. Only one of the participants has a significant difference at Beta wave. The results suggest that the tendency of alpha and beta/alpha ratio of each individual is stable.

VI. CONCLUSION

This paper compared the developer's brain wave when they succeeded and failed to find an implementation strategy. The following were the main findings: EEG has an effectiveness as an index for classification of programmers who fail to find an implementation strategy. More specifically, the result describes that EEG during task contains significantly larger alpha wave power and beta/alpha ratio when success to find an implementation strategy. The result also shows similar tendency of a brain wave after task. These results suggest that developer's EEG during and after task is useful metric to distinguish developers struggling to find appropriate strategy.

We also analyzed the effect of individual differences. The analysis showed that more than half of participants have shown significantly larger alpha wave and beta/alpha ratio when they succeeded to find an implementation strategy. Therefore, measurement of alpha wave and beta/alpha ratio is useful to classify struggling developers, even though EEG can be affected by individual difference and other artifacts. Classifying developer’s state via EEG allows quick grasp of worker/student who needs supervisor’s help.

As future work, chronological frequency component analysis is an interesting research topic. The frequency component during (and after) programming task will change with time progress. Clarifying the periods of EEG that contains a strong influence of task leads more accurate and efficient classification. Real time identification of struggling developer is another interesting theme. Several machine learning techniques such as random forest and SVM are useful for in-situ support on Integrated Development Environment (IDE) in training.

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Table.1. EEG component of each subject

Subject	Alpha			Beta			Beta/Alpha		
	success	fail	p	success	fail	p	success	fail	p
1	0.754	0.009	0.036*	0.579	0.027	0.138	1.104	3.722	0.297
2	0.270	1.230	0.368	0.686	1.499	0.019*	2.496	1.096	0.116
3	1.186	0.256	0.000	0.464	3.563	0.100	0.349	13.302	0.206
4	1.212	0.025	0.005*	0.330	0.206	0.099	0.613	7.156	0.003*
5	0.206	0.028	0.235	0.195	0.046	0.482	2.004	1.656	0.670
6	1.071	0.044	0.001*	0.591	0.077	0.375	0.944	1.488	0.877
7	0.529	0.442	0.084	0.781	0.618	0.506	2.860	4.129	0.991
8	0.907	0.036	0.005*	0.803	0.370	0.306	0.844	13.488	0.326
9	1.219	0.001	0.000*	0.066	0.033	0.213	0.079	40.942	0.120
10	0.001	0.001	0.343	0.004	0.005	0.403	7.306	19.665	0.912
11	0.176	0.357	0.183	0.709	0.987	0.375	3.501	24.318	0.519
12	0.856	0.029	0.077	0.296	0.184	0.330	0.632	5.974	0.546
13	0.941	0.067	0.009*	0.418	1.164	0.090	0.755	12.140	0.030*
14	0.442	0.541	0.267	0.732	0.811	0.450	1.469	3.992	0.891
15	1.101	0.344	0.000*	0.800	1.231	0.242	0.913	3.206	0.348
16	1.073	0.031	0.003*	1.024	0.508	0.108	0.633	16.223	0.024*
17	0.187	0.891	0.396	0.207	0.786	0.974	1.026	1.170	0.386

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