Estimation of Intellectual Concentration States using Pupil Diameter and Heart Rate Variability

Kaku Kimura, Shutaro Kunimasa, You Kusakabe, Hirotake Ishii and Hiroshi Shimoda
Graduate School of Energy Science, Kyoto University, Kyoto, Japan

Keywords: Intellectual Concentration States, Classification Learning, Physiological Indices, Pupil Diameter, Heart Rate Variability.

Abstract: Although modern society has improved the value of intellectual work, its objective and quantitative evaluation method has not been established. In this study, the authors have focused on physiological indices such as pupil diameter and heart rate variability which are supposed to be influenced by their cognitive load in office work, and an estimation method of intellectual concentration states from the measured indices has been proposed. The concentration states to be estimated in this study are one of three states when giving three kinds of cognitive loads which are high, medium and low. As the result of the experiment where intellectual concentration states of 31 participants were estimated, the accuracy was 57.3% in average and it was significantly higher than random estimation ($p < 0.001$). It was also found that those who had no clear physiological response caused by the difference of cognitive load or those who showed different physiological response when measuring in different time tended to be low estimation accuracy.

1 INTRODUCTION

In modern information society, most human activity in office and laboratory is intellectual work. It is expected that the efficiency of work performance, that is, intellectual productilvity get improved by reviewing office environmentand companies can get a lot of economic benefit. In this way, intellectual work is an important factor in modern society. In order to evaluate it, various studies have been conducted. For example, an evaluation method based on visual task has been proposed (Kosuke et al., 2000)(Wargocki et al., 2000). It is, however, difficult to evaluate intellectual work productivity directly due to the difference between the visual task and real office work. On the other hand, there are another evaluation method using physiological indices by biological response of human beings. In the case of this method, it is possible to measure on time while office worker is actually engaged. Since the work efficiency of simple intellectual work sharing the majority of office work is closely related to the intellectual concentration state when cognitive load is applied, it is possible to indirectly evaluate intellectual productivity by estimating the intellectual concentration state when giving a cognitive load. It is known that physiological indices are closely related to cognitive load of human beings (Tryon, 1975)(Jorna, 1992) so that they can be effective indices. Considering these backgrounds in this study machine learning methods are applied where training data is created by conducting classification learning about each individual physiological measurement data while the intellectual concentration states of office workers are changed. The purpose of this study is to propse a method which can estimate intellectual concentration state of office workers. As shown in Figure 1, heart rate variability and pupil diameter were employed as the physiological indices for intellectual concentration estimation. Classification learning method was employed in order to derive trained model for the estimation, and estimated the test data based on the trained model. If this method

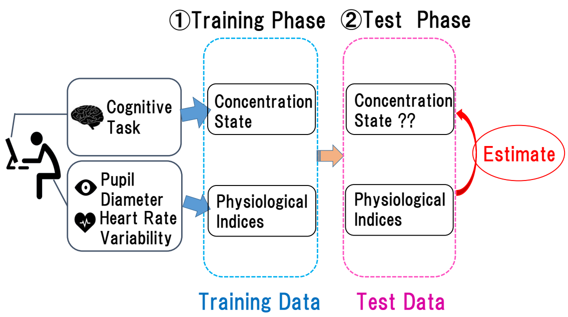

Figure 1: Outline of this study.

Kimura, K., Kunimasa, S., Kusakabe, Y., Ishii, H. and Shimoda, H.
Estimation of Intellectual Concentration States using Pupil Diameter and Heart Rate Variability.
DOI: 10.5220/0006928800620069
In *Proceedings of the 2nd International Conference on Computer-Human Interaction Research and Applications (CHIRA 2018)*, pages 62-69
ISBN: 978-989-758-328-5

is shown to be useful, it is possible to estimate intelligent concentration states of real office workers. It is also expected to be applied to the evaluation of intellectual productivity.

2 ESTIMATION METHOD

2.1 Cognitive Activity and Physiological Indices

It is known that there is a close relationship between physiological reponse and coginitive activity (Tryon, 1975)(Jorna, 1992), and especially pupil diameter and heart rate variability are easy to change as cognitive activity changes (Eckhard H. Hess, 1964)(Tsukahara et al., 2016)(Mulder and Mulder, 1981). In addition, it is expected that non-contact measurement technology is established on the every indices in the future (Sakamoto et al., 2015), and that the influence of wearing measurement instruments on physiological indices can be ignored. Therefore, pupil diameter and heart rate variability were employed in this study.

2.1.1 Pupil Diameteer

In the field of psychophysiology, it is known that pupil diameter changes by various cognitive activity condition (Eckhard H. Hess, 1964)(Tsukahara et al., 2016), so that it is considered that pupil diameter is effective as a measurement index also in this study. The variables used for the estimation were left eye and right eye pupil diameter.

2.1.2 Heart Rate Variability

In the field of psychophysiology, heart rate variability is used as indices which reflect cognitive load, stress, and emotion (Mulder and Mulder, 1981). It is considered that changes in intellectual concentration states have an effect on changes of variability, and it can be also an effective measurement index. The variables used for estimation were 4 elements. They are heart rate(HR), LF power, HF power, the ration of LF to HF(LF/HF), which are often used in various studies on cognitive load theory. In this study, an electrocardiogram (ECG) measurement method is adopted, which is the most reliable method for heart rate measurement. Electrode was attached to each of the left flank and the right neck muscle, and the waveform of the electrocardiogram was observed. Heart rate was calculated by measuring the RR interval from the R wave of the ECG and determining the inverse number. Regarding feature value extraction, one section has 60 second long, in which the power spectrum of the LF band falls for at least 3 cycles. Then, while shifting this section every 30 seconds, the average value calculated from each section was taken as the feature value of the section. Regarding the pupil diameter data, in order to make the time series of data unified with the heart rate variation, the feature value section to be extracted was set to be the same as the heart rate variability.

2.2 Estimation Method of Intellectual Concentration States

In this study, the cognitive load was changed by distinguishing solution method of cognitive tasks. Then, multiple physiological indices data from cognitive task was learned in order to estimate the intellectual concentration state according to the cognitive load. Although Classification learning is usually based on two binary classification, classification of three or more classes is possible by applying multiclass classification method called ECOC method (Dietterich and Bakiri, 1995). This method is employed in this study to estimate the intellectual concentration state classified into three types. Various classification learning methods such as SVM and KNN were applied to physiological data. A list of all the 11 classification methods applied in this study is shown in Table 1. Estimation of test data is performed based on trained models classified by these methods. MATLAB (Inc MathWorks,) was used for analysis and estimation of measurement data. The evaluation method of estimation accuracy is explained in section 4.1

Table 1: List of classification methods.

	Classification Method	Remarks
1	Decision Tree	
2	Linear Classifier	
3	Quadratic Classifier	
4	Linear SVM	
5	Quadratic SVM	
6	Cubic SVM	
7	Fine Gaussian SVM	= 0.6
8	Middle Gaussian SVM	= 2.4
9	Row Gaussian SVM	= 9.8
10	Fine KNN	k = 1
11	Row KNN	k = 10

3 EXPERIMENT

3.1 Purpose

The purpose of this experiment was to extract physiological indices data by measuring pupil diameter and heart rate during intellectual work and to evaluate estimation accuracy by performing various classification learning method shown in Section 2.2 .

3.2 Method

3.2.1 Cognitive Task

In this study, Receipt-Classification Task was applied as the task used for estimation of intellectual concentrate states. It is a cognitive task in which three items of information on the date, amount of money and business type of the displayed receipt was classified and they continues to answer the corresponding option until the time limit. All operations are performed by moving a mouse and left clicking. The examples of the task displays are shown in Figure 2 and Figure3. In case of Figure 3, the date is “27th”, the amount is “4,600 JPY”, and the company is “Higuchi Postal Carrier”, the part corresponding to “Day 21-30”, “-5000 yen”, and ”Transportation/Post” is the correct answer. The reasons for employing the Receipt- Classification task are as follows; First, the task difficulty level is almost uniform. In this study, the change of the solution method such as the solution speed of tasks is considered as the change of intellectual concentration state and estimate the concentration state, so it is necessary to unify conditions such as difficulty level of task. Second, the task reflects the processing capability required for simple intellectual work in the actual office. The ability necessary for simple intellectual work is supposed to be the numercical processing ability such as data entry or graph creation, and the linguistic processing ability such as document preparation. Even in this study assuming application to actual work, these two capabilities are required when solving the tasks. For the above reasons Receipt-Classification task was used in this study.

3.2.2 Control of Performing Task

There is a close relationship between cognitive load and intellectual concentration state, and the more concentrated the worker is, the more taken cognitive load. In this study in order to estimate the intellectual concentration state when giving a cognitive load, it is necessary to change the intellectual concentration state in a state where various amounts of cognitive load are given. In this experiment, therefore, the answer method of task was set to change by intentionally controlling cognitive load . A list of relationship between task type and intellectual concentration states is shown in Table 4. First, two kinds of answer pace of tasks, slow pace and fast pace were set, which are “Task A: slow pace” and “ task B: fast pace”. The answer pace of each participant was decided by themselves. In addition, “Task C: Click” was introduced as a control condition of Task A and Task B, which is a task that gives no cognitive load, Click is a task of repeating mouse clicks on appropriate places without the Receipt-classification. Even in this task, since physical actions such as looking at the screen and operating the mouse is similar to the task A and B, it is considered that the factors affecting the physiologi-

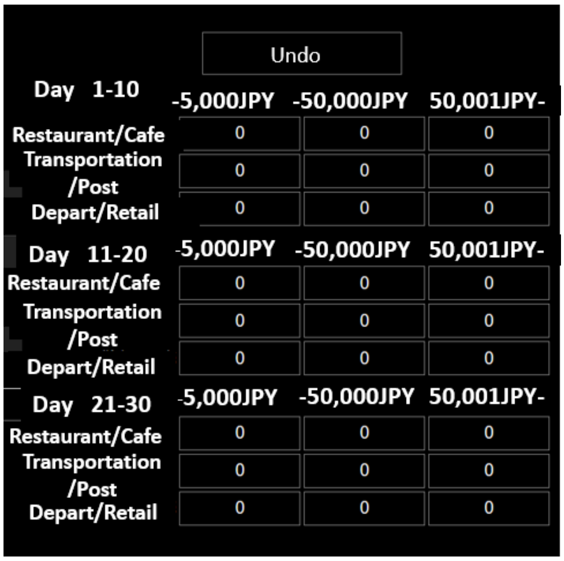

Figure 2: Display for Reccipt-Classifiation Task.

Figure 3: An example of a receipt.

cal response other than the difference in the cognitive load are equivalent to those of the task A and B. For the above three kinds of answer methods, task A was set as the cognitive load "medium", task B as the cognitive load "high", and task C as the cognitive load "low". The total time was set to 5 minutes because it is considered that feature values for estimation should be sufficiently extracted, and the same concentration state can be maintained during task. The task performance and correct answer rate are not the target of the estimation in the experiment .

3.2.3 Experimental Environment

The experiment was conducted an experimental room of Kyoto University. The room temperature during the experiment was controlled to 251.0, thesound noise was controlled to less than 50 dB, and the illuminance on the desk was set to approximately 550 lux.

3.2.4 Measurement of Physiological Indices

Pupil diameter and ECG were employed in this experiment. The pupil diameter was measured by an infrared eye tracking camera, faceLAB5 (Seeing Machines,). The installation position of faceLAB5 camera and the camera angle are shown in Figure.4. The height and position of the chair was adjusted for each participant so that the head of the participant can be recognized correctly. since it is necessary to perform face recognition as precisely as possible, a jaw table was installed for suppressing the movement of the head. The ECG was measured by Polymate AP216. The electrodes were placed on a left rib and a right clavicle where R wave is easy detected without body motion artifact. As a noise signal removal, the cutoff frequency of the low-pass filter was set to 100 Hz, and a notch filter of 60 Hz was set as a hum noise elimination from the commercial power supply.

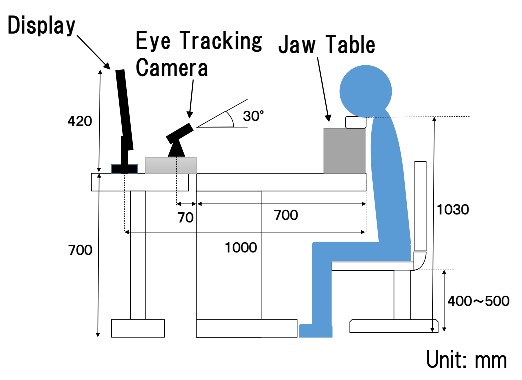

Figure 4: Position of a participant and experimental devices.

Table 2: Experimental schedule.

Duration(min)	Content
10	Introduction and Explanation
10	Setting of Electrodes and Eye Tracking Camera
10	Task Practice
18	Set1
5	Break Time
18	Set2
10	Removal of the Instruments /Quastionnaire

Table 3: Protocol for each set.

Duration(min)	Protcol
1	Rest
5	*Task1
1	Rest
5	*Task2
1	Rest
5	*Task3

*The order of task answer methods was random for each participant

3.2.5 Experimental Protocol

The experiment was conducted in December 11th to 27th, 2017. The experimental schedule and the task protocol of each set are shown in Table 2 and 3 respectively. Each participant conducted two sets of the task. As shown in Table 3, Each set contained rest time for 1 minute, task time for 5 minutes and they were repeated 3 times. For each set, Receipt-Classification task was conducted for 5 minutes with three kinds of answer methods shown in Table 4. The order of task answer methods was random for each participant in order to cancel order effect of the tasks. In the rest time, white '+' mark was displayed at the center of the screen for 1 minute. A simple questionnaire was given to the participants after the experiment. It was used as a reference for the detail interpretation of experimental results.

3.2.6 Participant

Participants were 31 male university students. They were (1) those whose mother tongue is Japanese, (2) not wearing glasses. Regarding the condition of (2), it was observed that the accuracy of pupil diameter measurement of participants wearing glasses sometimes deteriorated in the preliminary experiments. Therefore, in order to keep the measurement accuracy, this condition was set for the purpose of removing participants who wore glasses in advance.

Table 4: Relationship between task type and intellectual concentration states.

Task Type	Details	Cognitive Load	Concentration States
Task A (Slow Pace)	Solve the Receipt-Classification Task as Slow as Possible	Middle	Somewhat Concentrated
Task B (High Pace)	Solve the Reccipt-Classification Task as Fast as Possible	High	Very Concentrated
Task C (Click)	Conduct the Click Task (Do Not Solve the Receipt-Classification Task)	Low	Not Concentrated at All

4 RESULT

In this experiment, six out of the 31 participants were excluded from the later analysis as invalid data.The reasons why there were invalid data was because their heart beat data was lost due to the failure or irregular power off of the ECG measuring device, or pupil diameter data was lost due to their dozing during measurement. Finally 25 participants excluding the above six were analyzed. 10 out of 25 participants were interrupted half way because an error occurred in which the response of the task was interrupted at the transition of the task screen, and their measurements restarted from just before the error occurred. However, since there was no data loss of these participants, their measured data were included in the later analysis.

4.1 Evaluation Method of Estimation Accuracy

60 second pupil diameter data and heart rate data extracted as a frame and the frames were shifted every 30 seconds, and the average value of each frame excluding the beginning 30 seconds was taken as the extracted feature value. In this experiment, the total time of each task was set to 5 minutes, so the number of feature values per variable was 24. The explanatory variables are the left pupil diameter, the right pupil diameter, heart rate, LF, HF, LF / HF in total, and the objective variable is the type of tasks described in Table 2. The ratio of the number of the objective variables that can be correctly estimated, that is, the correct estimation rate, is evaluated as estimation accuracy in this method.

Next, an evaluation method of estimation accuracy will be described. First, for all 24 training data, all classification learning methods shown in Table 2 were applied. Then, the highest generalization performance for each participant was defined as a trained model of the participant. Finally, an unknown test data of the participant was estimated based on the model and the estimation accuracy was calculated. In this experiment total 2 sets of similar protocols were carried out. Thus, estimation accuracy in this study was defined as average value of accuracy when setting set 1 as training data, set 2 as test data and accuracy when setting set 1 as test data, set 2 as training data. The cross validation method was used to evaluate the generalization performance of the trained model. Generalization performance of trained models of all valid data was 91.1% in average. The most applied classification method was linear classifier, and at the next point was SVM.

4.2 Estimation Accuracy of Intellectual Concentration States and Disccusion on Estimated Error

By using the estimation method discribed in 4.1 section, the estimation accuracy of all valid test data wa 57.3% in average. It was significantly higher than the random expected value ($p < 0.001$). However, the percentage of correct answer was depending on the individual participants. In the following, giving representative examples of participants who were high in correct answer rate and those who were low, and discuss the differences in estimation results.

First, considering the participant who was estimated with the highest accuracy with a correct answer rate of 88%. Figure 5 shows a scatter diagram for each physiological index where the horizontal axis shows those of set1 while the vertical axis shows those of set2 for each of the 8 feature values in each of the three intellectual concentration states. If the same feature value appeared between set1 and set2, a feature point is displayed on the straight line y = x. In the case of this participant, obvious differences of pupil diameters and heart rate were shown between three concentration states, where they increased when the cognitive load of the task increased. Regarding LF and HF, although there was no such obvious differences between concentration states, there was a tendency to show the smallest value in task B: very concentrated status. From the above results, in case of this participant it seems that the difference in intellectual concentration state due to the task difference appeared in

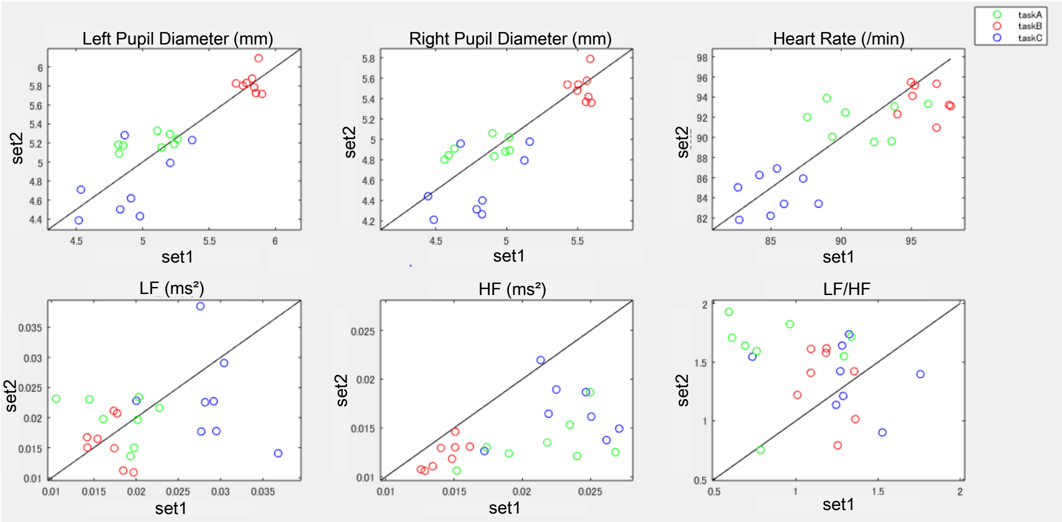

Figure 5: Scatter plots between two set about physiological indices in ex1.

the different physiological responses, and estimation accuracy got higher because of similar responses between set 1 and set 2.

Next, considering the participant whose estimation accuracy was the lowest with a correct answer rate of 23%. A scatter diagram of each feature value for each index is shown in Figure 6. In the case of this participant, no particular trend due to difference in cognitive load was found in any indicies. In this participant, the generalization performance of the trained model is as low as 77%. Therefore, it is supposed that it is difficult to create a trained model by classification learning and the estimation of test data could not be done correctly because the difference of the intellectual concentration by the difference of tasks tends not to appear as a physiological response.

Finally, considering another example of participant who had a low correct estimation rate. A scatter diagram of the feature values of each index is shown in Figure 7. Despite the fact that the generalization performance of the trained model was as very high as 98%, the correct estimation rate of the test data was as low as 42%. As shown in Figure 7, there is a difference in the left and right pupil diameter, which is considered to contribute to the trained model construction. However, each feature value is distributed to the lower right of the straight line y = x. That is, the pupil diameter decreased at set 2 compared with set 1 in any time frame. Taking average of the pupil diameters of every set of all participants, in task B with very concentrated state, their pupil diameters decreased significantly in set 2 compared with those in set 1. It is supposed that they contracted due to the decrease of cognitive load by learning effect. When set 1 is set as training data and set 2 is as test data, task B is incorrectly estimated as task A and task A is as task C. Thus, it is suppossed that even when different physiological responses appear when measured at different times, a deviation may be seen in the physiological index data and an incorrect concentration state may be estimated.

5 CONCLUSIONS

In this study, as a basic study for developing quantitative evaluation method of intellectual concentration, a method was propsed and examined to estimate the intellectual concentration state of the worker by measurement of physiological indices, and an experiment was conducted to evaluate the estimation accuracy of the method. As the result of the experiment, the estimation accuracy was 57.3% in average, which was significantly higher than the random expected value ($p < 0.001$). Some of the participants showed extremely high value of estimation accuracy, while those who did not clearly show differences in cognitive loading in physiological responses, or those with different physiological responses showed low estimation accuracy. Particularly with regard to the pupil diameter, a large change was observed due to the difference in cognitive load, and it is supposed that the measurement value was varied during the measurement at different time due to the contraction of the pupil by learning effect.

In the future, it is necessary to devise various ideas such as explore additional physiological responses that can contribute to the estimation by increasing the measurement indices, or examining the method of correcting the deviation of the values when measured

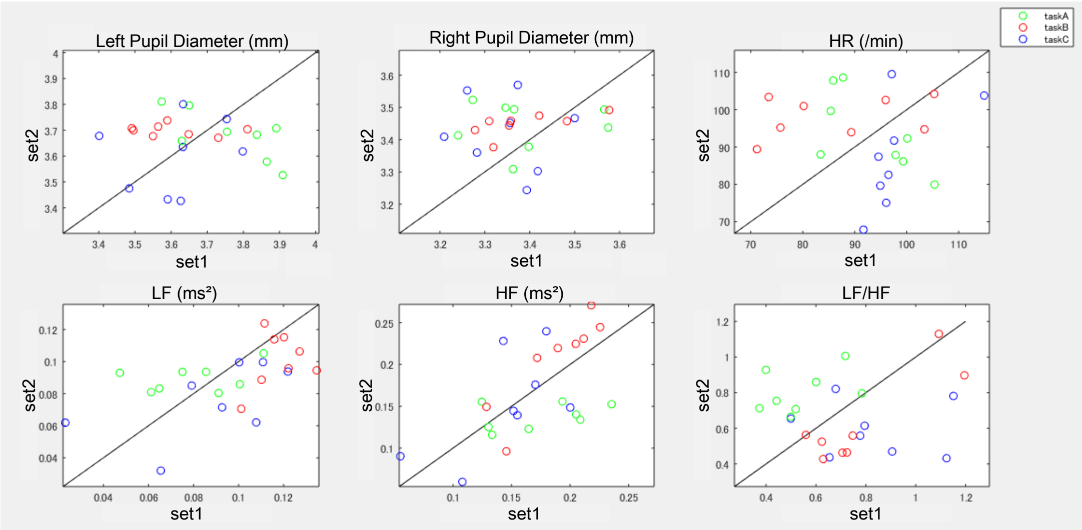

Figure 6: Scatter plots between two set about physiological indices in ex2.

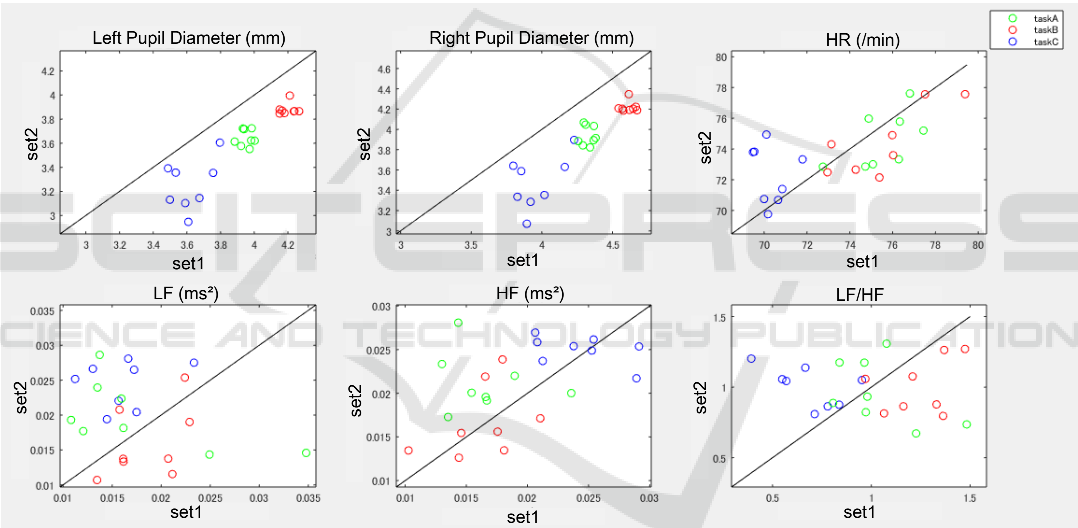

Figure 7: Scatter plots between two set about physiological indices in ex3.

at different times. In this study, since experiment was conducted with participants only for men university students, it is also necessary to verify the influence on the estimation accuracy due to the difference in the attributes of the participants. Furthermore, in this study, the intellectual concentration states are estimated by the cognitive load amount set for each answer method of the Receipt-Classification Task, and the intellectual concentration states in actual work cannot be directly estimated by physiological responses. In the future, it is necessary to confirm the effectiveness of the present estimation method in tasks other than Receipt-Classification Task and to study the relationship between cognitive activity and physiological responses.

ACKNOWLEDGEMENTS

This work was supported by JSPS KAKENHI Grant Numbers JP17H01777.

REFERENCES

Dietterich, T. G. and Bakiri, G. (1995). Solving multiclass learning problems via error-correcting output codes. *Journal of Artificial Intelligence Research*, 2:263–286.

Eckhard H. Hess, J. M. P. (1964). Pupil size in relation to mental activity during simple problem-solving. *Science*, 143(3611):1190–1192.

Inc MathWorks. MATLAB. http://www.mathworks .co.jp/products/matlab.html. (Accessed May. 2018).

Jorna, P. G. A. M. (1992). Spectral analysis of heart rate and psychological state: A review of its validity as a workload index. *Biological Psychology*, 34(2):237–257.

Kosuke, U., Koutarou, O., Kazune, M., Hirotake, I., and Hiroshi, S. (2000). Process in evaluation index of intellectual productivity based on work concentration. *Lecture Notes on Software Engineering*, 2(1):635–640.

Mulder, G. and Mulder, L. J. M. (1981). Information processing and cardiovascular control, psychophysiology. *Psychophysiology*, 18(4):392–402.

Sakamoto, T., Okumura, S., Imanishi, R., Taki, H., Sato, T., Yoshioka, M., Inoue, K., Fukuda, T., and Sakai, H. (2015). Remote heartbeat monitoring from human soles using 60-ghz ultra-wideband radar. *IEICE Electronics Express*, 11(25):1–6.

Seeing Machines. faceLAB 5. http://www.ekstrem-makina.com/EKSTREM/product/facelab/index.html (Accessed May. 2018).

Tryon, W. W. (1975). Pupillometry: A survey of sources of variation. *Psychophysiology*, 12(1):90–93.

Tsukahara, J. S., Harrison, T. L., and Engle, R. W. (2016). The relationship between baseline pupil size and intelligence. *Cognitive Psychology*, 91:109–123.

Wargocki, P., Wyon, D. P., and Fanger, O. P. (2000). Productivity is affected by the air quality in offices. *Proceedings of Healthy Buildings*, 1(1):635–640.