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Estimation of Student Understandings from Pulse Wave Changes Caused by Load in Preparatory Course

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***Abstract*—We propose a method to estimate whether student hold knowledge on the contents and tasks of the class, using cognitive load and mental load. We estimate the cognitive load of the student using a pulse wave and the pulse change.The mental load can be estimated from the activity of the autonomic nerve. In order to clarify student knowledge on course contents, we estimate student schemata from the load on the student.We conducted an experiment, preparing 2 kinds of tasks; S1 task can be answered with student schemata, while S2 task cannot be answered with student schema. Through the experiment using the proposed method, we classified tasks given to students into S1 tasks and S2 tasks.It was possible to estimate the student schemata from the standard deviation of the heart rate.This method makes it possible to figure out student understanding earlier than traditional knowledge measurement method.**

I. Introduction

FLIPPED CLASSES are introduced to actual educational classes, as open teaching materials, e-learning, and MOOCs(Massive Open Online Courses) spread[1][2]. In Flipped classes, learners prepare before lessons, based on open teaching materials and assignments. Meanwhile, in the classes, the teachers check the learners' knowledge. If they find contents the students fail to understand, they explain the contents.

In face-to-face classes, the learners study at designated places such as classrooms and at fixed times. The learners review the lesson contents after the lesson. They engage in homework to develop their learning. However, in face-to-face classes, teachers put their main points in giving knowledge to learners. Learners also concentrate on acquiring knowledge. As a result, there are concerns that initiative learning of students would decline, because they cannot enhance interests in acquiring new knowledge and problem solving skills.

In the flipped classes, there is no constrains on place or time for learners to prepare the content of the class. They can learn at any place and any time suitable for each learner. The learners can determine contents to study and the learning time for themselves. In addition to that, since the learners study the prepared knowledge in classes, they can increase opportunities to use the knowledge. Through these aspects, flipped classes are expected to have good effects to increase the learning time and motivation of learners, to promote initiative learning. Some colleges in U.S. have introduced flipped classes, showing the effect of improving learning motivation and raising the completion rate of students [1][2].

However, there are some defects for flipped classes. For example, in flipped classes, it is not secure the learning time[3]. Since teachers cannot grasp the comprehension degree of individual learners, they cannot conduct classes suitable for each of learners. If assignments or class content given to students at the time of preparation is too easy, learners would acquire less knowledge, which makes the learning efficiency low. Therefore, it is necessary for teachers to grasp the knowledge acquired by learners at the time of preparation and the knowledge they have already acquired, in order to make the learning more efficient and the progress of the flipped classes smooth. The paper proposes a method to estimate whether or not learners hold knowledge about lesson contents. We focus on the cognitive load in learner during preparation and the mental load due to emotional changes such as impatience and tension. Existing studies have revealed that when cognitive load or emotion changes, the sympathetic and parasympathetic functions change, which causes the pulse wave to fluctuate. Based on the results, this method uses a pulse wave sensor to measure the cognitive load and the mental load of learners. We extract learners' features representing cognitive load and mental load from various data elements of pulse waves and pulse fluctuations. In the experiment using this method, we have found that the standard deviation of the heart rate of the learner at the time of problem solving is effective to discriminate whether the learner holds knowledge on the given task.

In this paper, we introduce related research in ChapterII. ChapterIII explains the method proposed in this research. ChapterIV gives experiments and evaluations. ChapterV discusses the experimental results. ChapterVI summarizes this research.

II. Existing Research

Learner's stumbling and troubles occur at the time of preparation in the flipped classes, because of lack of knowledge of learners on tasks and contents in classes. At this time, the learner is overloaded. The overload makes the leaners avoid their learning. On the contrary, learning effect is low when they are forced to answer the task they have already achieved. This task has low cognitive load for learners. More than one researches have been conducted to measure the load on learners at the time of learning, aiming at providing them with appropriate load according to the ability of the learners and reducing the burden on learners[5].

A. Existing research on cognitive load

The cognitive load theory[4] points out there are working memory and long term memory (LTM) in the human memory structure for learning. The working memory is a memory which has limited capacity and holds information temporarily. When humans perceive experiences and knowledge, burdens are imposed on the working memory. Schema is stored in LTM. A schema is a onein which human experiences and knowledge are accumulated and organized.

There are three types of cognitive loads which occur during learning[6]. The intrinsic cognitive load is the one caused by task itself such as difficulty level and complexity in task solving. It is defined by the number of factors considered in learning. Although it is not related to the task itself, the extraneous cognitive load occurs in recognition of design and format of the teaching material used for learning. The germane load occurs when learners are establishing schemas to fix the knowledge in problem solving and memorization. Since these three kinds of cognitive loads are additive relationships, they never appear in a completely separate way. Many studies try to measure these three types of cognitive loads individually, operating experiment environments[8].

B. Measurement of cognitive load

The cognitive load is measured using subjective evaluation, physiological index, performance index such as the learner ' s exam results. Mizuno et al[9]. measured cognitive load using reaction time in problem-solving learning as a performance index. In order to measure the learner's load on line at an early stage during learning, it is effective to acquire a physiological index using a sensor. Examples of physiological indices used for measuring cognitive function include skin conductance response, pupillary reaction, and heart rate[11]. Tsunoda et al[13] measured cognitive load at mental load work of brain workers, using heart rate variability as a physiological index.

Most of studies measure the cognitive load based on whether or not a load is applied. There are few studies which measure the cognitive load, focusing on schema construction. We cannot know whether learners hold knowledge on learning contents from the cognitive load of learners at their learning time.

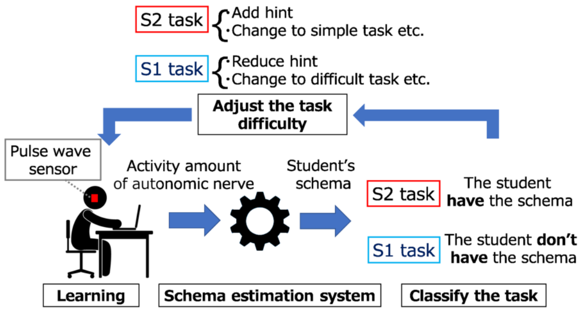

Fig. 1. The outline of the schema estimation system

III. Estimation of Learner's Schema Using Load on Learner

A. Improve flipped classes by estimating learner's schema

From ChapterII, There are many researches to estimate cognitive load from pulse fluctuation, and it can be estimated with high accuracy. However, few researches focus on the relationship between pulse fluctuation and the schema held by the learner. Therefore, in this research, we propose a system which classifies whether or not the learner holds the schema for the task from the pulse wave and the pulse fluctuation at the time of answer the task by the learner. Figure1 shows the outline of the system (schema estimation system) that estimates the schema held by the learner using this method.

The learner's learning content is improved by identifying from learner's pulse wave and pulse fluctuation whether it is a task that can be answered by the learner's schema. The procedure is shown below.

1) By using the pulse wave sensor, acquire pulse wave and pulse fluctuation during answer task of learner.
2) Analyze pulse wave fluctuation and pulse fluctuation of the acquired by the learner, and calculate 18 variations of learners' autonomic nerves.
3) From the calculated 18 variations of the learner ' s autonomic nervousness, it is identified whether the task given to the learner is a task or not that can be answered by the learner's schema.
4) When it becomes possible to grasp the schema held by the learner from heart rate variability, it is possible to identify whether learners are able to organize knowledge on the task. And it can be done earlier and in real time than traditional knowledge measurement methods such as hearing and testing.

Through these procedures, depending on the schema held by the learner, it is possible to support such as giving hints or changing the difficulty level of the task. And it is possible to improve the learning efficiency at the time of preparation in the flipped class.

B. Relationship between learner's schema and cognitive processing

In this research, we focus on differences in cognitive processing at the time of solution of tasks that can be answered

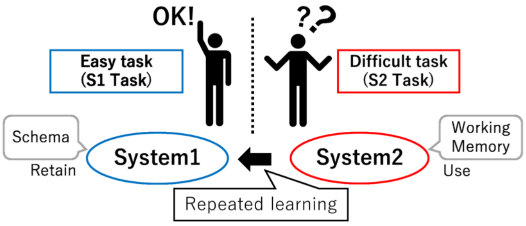

Fig. 2. Cognitive processing when the learner holds the schema and does not hold it

by the learner's schema and tasks that can not be answered. Figure2 shows how cognitive processing is performed when learners answer tasks. There are two ways of human cognitive processing, System 1 and System 2 proposed by Daniel Kahneman et al[14].

System 1: This Cognitive processing that can automatically understand without much perceptual activity. Because the experiences and the knowledge about the task are already organized and structured as a schema and it is kept in long-term memory. System 2: This Cognitive processing that consciously understands the objects. Because, it is unfamiliar to experiences and knowledge concerning the object to be recognized, construction of the schema is not done, and perceptual activity is necessary for understanding.And, by repeatedly performing cognitive processing of System 2, a schema related to the experiences and knowledge is constructed, and cognitive processing of System 1 can be perceived. Replacing the ideas of System 1 and System 2 with learning, tasks can be divided into the following two types.

- The tasks that the learner can construct the schemata has been able to organize the knowledge on the tasks, and the tasks that do not require much perceptual activities to answer.
- The tasks that learner have not been able to construct schemata have not been able to organize knowledge about the tasks, and the tasks that require much perceptual activities to answer.

Therefore, in this research, the tasks that can be answered by the schema held by the learner are set as S1 tasks, and the tasks difficult to solve by the schema held by the learner are set as S2 tasks.

C. Estimation of load using learner's pulse wave and pulse fluctuation at task solving time

When solving the S1 task, the cognitive load on the learner is small, and the usage of the working memory is small. In solving the S2 task, the cognitive load on the learner is large, and the working memory is pressed. Also, when the learner solves the S2 problem, it is difficult to solve the S2 task, and emotional changes such as impatience and tension appear[10]. Therefore, by using pulse fluctuation that can estimate cognitive load and emotion, S1 task and S2 task are identified. It is known that the cognitive load on learners at task solving time can be estimated from pulse wave and pulse fluctuation of learners [11].

In addition, the load due to mental factors such as impatience and tension of the learner can be estimated from autonomic nervous fluctuation that can be calculated from the pulse wave or pulse fluctuation of the learner. As a method of acquiring the pulse rate and pulse fluctuation of the learner, there is a method of attaching a pulse wave sensor to the learner. By using a pulse wave sensor, it is possible to measure pulse wave and pulse fluctuation easily from the fingertip and earlobe, so there is little extra load due to attaching a pulse wave sensor to the learner. In this research, we estimate the load at the time of task solving by the learner from the pulse wave and pulse fluctuation acquired by attaching the pulse wave sensor to the learner. By analyzing the acquired pulse wave and pulse fluctuation, we calculate the following nine variables which are indices of the autonomic nerve.

From the heart rate variability, the following components can be obtained; Heart Rate, RR Interval (RRI), TP (total of VLF, LF, HF), VLF (Very Low Frequency), LF (Low Frequency), HF (High Frequency), LF / HF(Indicator of sympathetic function), HFnorm(Expression (1)), LFnorm(Expression (2)). HFnorm, LFnorm are calculated by the following expressions.

$$HFnorm = (\frac{HF}{HF+LF}) \times 100 \quad (1)$$

$$LFnorm = (\frac{LF}{HF+LF}) \times 100 \quad (2)$$

We calculate the mean and standard deviation of the indices of these nine autonomic nerves and estimate the load on the learner when solving the tasks from the total of 18 variables.

D. Classification of tasks by machine learning

In this study, we classify tasks as S1 tasks or S2 tasks for learners, based on the difference between cognitive load and mental load on learners at the time of solving tasks of S1 task and S2 task. The S1 task and the S2 task are classified by machine learning. We use the variation of the autonomic nerves of the 18 learners written in SectionIII-C. As an explanatory variable and two kinds of tasks given to the learner as objective variables. There are two types of S1 task and S2 task. In this system, the S1 task and the S2 task are presented to the learner beforehand. At that time, acquire the variation amount of the learner's autonomic nerve, and use it as teacher data. Random Forest (RF)[15] with ensemble learning is used for machine learning algorithm. RF has a learning phase and an classification phase. In the learning phase, the RF constructs and learns an ensemble of decision trees using the obtained teacher data as training data. Thereafter, in the classification phase, each decision tree of RF classifies whether the task given to the learner from the load of the learner at the time of problem solving is the S1 task or the S2 task. And outputs the most frequent classification result.

E. Adjustment of tasks by estimating learner's schema

By using this method, it is possible to classify whether the task given at the preparation from the load at the time of task solving is the S1 task or the S2 task for the learner. If the task given to the learner is the S1 task, the learner can answer the task without much thinking. And the learner has little knowledge to acquire at the time of the task solving and poor learning efficiency. On the other hand, if the task given to the learner is the S2 task, the leaner needs perceptual activities for answers and it may be thought that the task is too difficult for the learner. Therefore, the learner can not answer the task, leading to problems such as learners' giving up and stumbling[18].

In order to improve the learning efficiency, it is required for the learner to have an appropriate difficulty level that the task is not too simple and not too difficult. Therefore, if the assignment given to the learner is the S1 task, the learner can construct the schema for the assignment and it is too easy, so it is necessary to adjust the task, such as reduction of hints and changes to applied task, in order to improve the learning efficiency. If the task given to the learner is the S2 task, the learner can not be able to construct the schema for that task and it may be too difficult. It is necessary to adjust the task, such as addition of hints and changes to more basic tasks, in order to set tasks suitable for learners[7]. Also, if the learner can correctly answer the S2 task, the learner repeatedly answers the same difficulty task, so that the learner can construct the schema and shift to the S1 task. By using this schema estimation system at the time of preparation in the flipped class, it is possible to adjust appropriate tasks and improve the learning efficiency of the learner.

IV. Purpose and Overview of Experiment

In this experiment, we examined whether the tasks presented to the learner can be identified as S1 task or S2 task, from the pulse rate and pulse fluctuation at the time of answer by the learner. The research participants were 12 university students aged 20 to 24 and answered six programming tasks as shown in Figure3. The programming task which was set by research participants is the selection problem of the filling format of programming code written in C language. And, we set questions of the following two patterns three questions at a time. And the task has the following two patterns. Each question was set three questions for each subject[16].

- S 1 Task(Tasks:1,2,3); Even if the learner does not understand the contents of the whole programming code, the question that can be solved if the leaner understands basic syntax
- S 2 Task (Tasks:4,5,6); The learners can not solve the question unless they understand the flow of the whole programming code or the functions in the code.

In order to avoid stress which is unrelated to the solution of the programming task, we did not set time limit of answer time. We allowed research participants to use the Web Browser and search when questions arise. To obtain the pulse

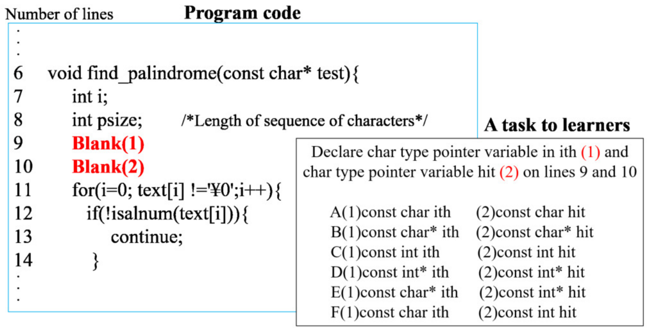

Fig. 3. Example of the programming tasks

rate and pulse fluctuation at the time of research participant programming solution, the research participant wears Vital Meter that a wireless earlobe pulse wave device manufactured by TAOS Laboratories. We get the following nine indicators from learners at the time of answering programming tasks. And calculate their mean and variance. The nine indicators are Heart Rate, RRI, LF, HF, LF / HF, VLF, TP, HFnorm, LFnorm. The sampling period in acquiring the pulse wave and pulse fluctuation was 1 kHz. Using these calculated values as explanatory variables, the task solved by the learner classifies either the S1 task or the S2 task based on the difference between the load amount when the learner solves the S1 task and the S2 task.

A. Confirmation of the validity of the tasks

In order to confirm the validity of the S1 task and the S2 task, the research participants were asked to answer the questionnaire. Questionnaire survey was conducted at the end of each task solution. We asked the questioner about the extent of perceptual activity such as calculation and memorization and answered in 6 steps of Linkert scale[17]. TableI shows the number of correct answers for each task. As a result of the questionnaire, the average of tasks 1, 2, and 3 were 3 points or less, and the average of 4, 5, and 6 were 4 points or more. Among the 12 research participants, the number of correct answers of tasks 1,2, and 3 were more than half, and the number of correct answers of tasks 4,5, and 6 were less than half. Based on the questionnaire result and the number of correct answers, it was confirmed that the tasks 1, 2, and 3 were S1 tasks because the learner needed less perceptual activity to the task solution and the correct answer rate were high. Also, tasks 4, 5, and 6 confirmed that the task were S2 because the learner needed perceptual activity to solve the problem and the correct answer rate were low.

B. Identification using Random Forest

In this experiment, using the analysis software attached to Vital Meter, the Heart Rate, RR Interval, LF, HF , LF / HF, VLF, TP, HFnorm, LFnorm, and a total of 18 variables of the mean and standard deviation of each of the nine variables. We used variance analysis to select effective variables from these 18 variables for classifying S1 task and S2 task. The

TABLE I
NUMBER OF CORRECT ANSWERS

Task Number	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
Number of correct answers	10	10	9	5	5	5

TABLE II
RESULTS OF VARIANCE ANALYSIS OF EACH 18 VARIABLES FOR CLASSIFYING S1 TASK AND S2 TASK

Explanatory variable		Heat Rate	RRI	HF	LF	LF/HF	VLF	TP	HF_norm	LF_norm
P value	Mean	0.6763395	0.7962887	0.3208657	0.2567065	0.9865234	0.5166716	0.3151521	0.0453415	0.3158083
	Standard deviation	0.0161003	0.2538482	0.1276715	0.443223	0.5046133	0.2063358	0.3018221	0.2666182	0.2666182

TABLE III
RESULT OF RANDOM FOREST USING STANDARD DEVIATION OF HEART RATE AND MEAN OF HFNORM

	S1 Task	S2 Task
S1 Task	1910	1701
S2 Task	1690	1899
Recall	0.531	0.528
Precision	0.529	0.529
F-measure	0.530	0.528

TABLE IV
RESULT OF RANDOMFOREST FOR EACH VARIABLE

Explanatory variable	Recall	Precision	F-measure
Standard deviation of Heart Rate	0.625	0.625	0.625
Mean of HFnorm	0.500	0.500	0.497

results of the analysis of variance are shown in TableII. This result shows a variable with a significant difference with the significance level set at 5%.

As a result of analysis of variance, it was shown that there is a significant difference between the standard deviation of heart rate and the mean of HFnorm. Explanatory variables were two variables, the standard deviation of heart rate and the mean of HFnorm. In order to compute the universal discrimination result, 12 leave-one-out cross verification were carried out by using Random Forest. Random Forest constructs a decision tree by randomly sampled training data. In order to reduce the influence due to bias in random sampling, 100 times identification was performed using Random Forest. TableIII shows the result of totaling the identification results by 100 times Random Forests. From the results of Random Forest, when using the standard deviation of heart rate and the mean of HFnorm as explanatory variables, the recall, precision, and F-measure were each about 0.53.

Also, 12 cross-validation was performed using Random Forest for each variable with the standard deviation of heart rate and the mean of HF norm. TableVII shows the results of identification using Random Forest for each variable. From the classification results using Random Forest, when the average of HFnorm is used as an explanatory variable, the recall, precision, and F-measure were each about 0.5. On the other hand, If the standard deviation of the heart rate is used as an explanatory variable, both the recall, precision, and F-measure were about 0.62, and the S1 task and the S2 task can be classified.

V. DISCUSSION

A. Deviation of heart rate

In ChapterIV, we conducted an experiment to distinguish the S1 task where learners hold the schema from the S2 task where learners do not hold the schema, using the pulse and pulse fluctuation. Based on the experimental results, we showed that the task given to the learner can be classified more accurately than random judges, using the standard deviation of the heart rate of the learner at the time of task engagement. The standard deviation of heart rate is high in tasks 4, 5, and 6, which falls into S2 task. It is conceived that the cognitive load imposed on the learners caused the high standard deviation of the heart rate. At the same time, we found the learners often sighs during the S2 task. It is conceived that the variation in heart rate was great because the heart rate is affected by the big breathing.

B. Dependence on individual learners

In this experiment, we did not take into consideration whether it is a high-load task or a low-task for individual learners. Here, we discuss this point. Using questionnaire, the tasks given to each learner were classified into high-load tasks or low-load tasks. We calculated the deviation value of the perceptual activity based on Likert scale 6. Tasks with deviation values of 50 or less were regarded as low load tasks, and the others high load tasks. TableV shows the task loads calculated from the questionnaire. For each of the 18 variables acquired at the time of the task engagement, we performed the variance analysis to examine significant differences between the high-load tasks and the low-load tasks. The results are shown in TableVI.

The results show that there was a significant difference in the standard deviation of the heart rate. We adopt the standard deviation of the heart rate as the explanatory variable to judge whether the tasks given to the learner were high-load ones. As a result of 12 cross-validation using Random Forest, the recall, the precision, and the F-measure were about 0.57, which means we cannot judge only with the standard deviation of the heart rate. Since the standard deviation of HF had the second lowest P value, we added the standard deviation of HF to explanatory variables. TableVII shows the results of 12 cross-

TABLE V
A QUESTIONNAIRE RESULT ON WHETHER EACH TASK IS A HIGH-LOAD TASK OR A LOW-LOAD TASK

Task Number	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
Number of learners who answered high-load tasks	2	2	1	11	11	7

TABLE VI
RESULTS OF ANALYSIS OF VARIANCE OF EACH 18 VARIABLES. IN ORDER TO FIND THE DIFFERENCE BETWEEN HIGH-LOAD TASK AND LOW-LOAD TASK.

Explanatory variable		Heart Rate	RRI	HF	LF	LF/HF	VLF	TP	HF_norm	LF_norm
P value	Mean	0.7330816	0.5980086	0.3791852	0.1775325	0.928875	0.6977778	0.2977588	0.227955	0.227955
	Standard deviation	0.0082179	0.4444583	0.0861439	0.5396019	0.7337266	0.6905658	0.7072911	0.5477441	0.5477441

TABLE VII
IDENTIFICATION OF A HIGH-LOAD TASK OR A LOW-ORDER TASK USING RANDOMFOREST

	Low-Load Task	High-Load Task
Low-Load Task	2807	1364
High-Load Task	993	2036
Recall	0.739	0.599
Precision	0.673	0.672
F-measure	0.704	0.633

validation using Random Forest. We identified it 100 times by Random Forest, to calculate the average.

The judgement using Random Forest taking the standard deviation of the heart rate and the standard deviation of HF as explanatory variables presents about 0.67 of the recall, the precision, and the f-measure. Based on the subjective difficulty level, it was possible to identify whether the tasks given to learners were difficult tasks or simple tasks.

VI. CONCLUSION

In this research, in order to give lesson contents and tasks suitable for learners at the time of preparation in the flipped class, we proposed a method to estimate whether the learner holds the schema related to the contents or not, using the cognitive load of the learner. We obtained cognitive load from autonomic nerve fluctuation calculated from learner's pulse wave and pulse fluctuation. By using machine learning, we identify whether the tasks given to the learner are hard ones from the cognitive load, to estimate whether the learner holds the schema for the tasks.

By experiment, we identified the difficulty level of tasks given to learners, using standard deviation of heart rate. As a result, the F-measure was about 0.62. By using the system proposed in this research, it is possible to adjust the contents of lessons and tasks for the learner, to improve flipped classes. In the future, in order to improve the accuracy, we will analyze data other than the pulse waves and the pulse fluctuation.

REFERENCES

[1] OnlineUniversities.com : "12 Inspiring Schools Using Khan Academy", http://www.onlineuniversities.com/blog/2012/04/12-inspiring-schools-using-khan-academy.

[2] The Chronicle of Higher Education : "California State U. System Will Expand MOOC Experiment", https://www.chronicle.com/blogs/wiredcampus/california-state-u-system-will-expand-mooc-experiment.

[3] Katsusuke Shigeta. : "Flipped Classroom : Educational reform utilizing information technology.", j-stage, Vol.56, No.10, pp.677-684, (2014).

[4] Sweller, John : "Cognitive load theory, learning difficulty, and instructional design.", Learning and instruction, Vol.4, No.4, pp.295-312, (1994).

[5] Schnotz, Wolfgang, and Christian KÃijrschner : "A reconsideration of cognitive load theory.", Educational psychology review, Vol.19, No.4, pp.469-508, (2007).

[6] Sweller, John, Jeroen JG Van Merrienboer, and Fred GWC Paas : "Cognitive architecture and instructional design." Educational psychology review , Vol.10, No.3 , pp.251-296, (1998).

[7] Paas, Fred GWC, and Jeroen JG Van MerriÃńnboer. "Instructional control of cognitive load in the training of complex cognitive tasks." Educational psychology review Vol.6, No.4, pp.351-37, (1994).

[8] DeLeeuw, K. E., Mayer, R. E. : A comparison of three measures of cognitive load: Evidence for separable measures of intrinsic, extraneous, and germane load. Journal of Educational Psychology, Vol.100, No.1, pp.223, (2008).

[9] Youichi Mizuno, et al. : " Experimental Investigation of Relationship between Cognitive Loads and Cognitive Processes in Learning through Problem Solving", SIG-ALST, Vol5, No.3, pp.7-11, (2016).

[10] Galy, Edith, Magali Cariou, and Claudine MÃľlan. "What is the relationship between mental workload factors and cognitive load types?." International Journal of Psychophysiology, Vol.83,No.3, pp.269-275, (2012).

[11] Ikehara, Curtis S. Martha E. Crosby : "Assessing cognitive load with physiological sensors." , System Sciences, 2005, HICSS'05, Proceedings of the 38th Annual Hawaii International Conference on. IEEE, pp.295a-295a, (2005).

[12] Mulder, Gijsbertus, Lambertus JM Mulder : "Information processing and cardiovascular control." Psychophysiology, Vol.18, No.4, pp.392-402, (1981).

[13] Keisuke Tsunoda et al. : "Estimating Cognitive Performance Change using Heart Rate Variability". Journal of Information Processing Society of Japan, Vol.57, No.8, pp.1835-1844, (2016).

[14] Kahneman, Daniel. : " Thinking, fast and slow." Macmillan, (2011).

[15] Breiman, Leo : "Random forests.", Machine learning, Vol.45, No.1, pp.5-32, (2001).

[16] Gerjets, Peter, Katharina Scheiter, and Richard Catrambone. "Designing instructional examples to reduce intrinsic cognitive load: Molar versus modular presentation of solution procedures." Instructional Science Vol.32,No.1-2, pp.33-58, (2004).

[17] Pollock, Edwina, Paul Chandler, and John Sweller. "Assimilating complex information." Learning and instruction, Vol.12, No.1,pp.61-86, (2002).

[18] Likert, Rensis. "A technique for the measurement of attitudes." Archives of psychology, (1932).