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Evaluating the Attitude of a Student in e-Learning Sessions by Physiological Signals

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***Abstract*: In this study, a novel approach towards the evaluation of students in e-learning sessions is regarded; the physiological responses of the students who were engaged in e-learning materials were investigated. Among a full battery of physiological signals, we focused on human hemodynamic activity, which is represented by the blood pressure. The past hemodynamic studies on mental stress showed that the difference in subject's stress coping style, i.e., active and passive coping, induced different hemodynamic responses. Such a variety of stress coping styles is also anticipated to be prevailing in attendees of e-learning course. In the experiment, the hemodynamic responses of the students who were engaged in the e-learning session were investigated with two considerably contrasting e-learning materials, one is characterized by an interactive material and the other is by non-interactive material. As a developing result, a particular hemodynamic pattern, which is involved in the subject's active coping, was observed in the interactive condition, and that of passive coping was observed in the non-interactive condition. These results thus led to an idea of evaluation of the "attitude" of attendees of e-learning courses.**

***Keywords*: e-Learning, Hemodynamics, Blood Pressure, Cardiac Output, Total Peripheral Resistance, Stress Coping**

I. Introduction

Recent developments of e-learning system enable students to have an opportunity to learn at anytime and even at anyplace of their choice. Against this background a high demand on the quality assurance of course materials in e-learning is emphasized. In the ordinary lecture at a school, teachers can keep close watch on the verbal and/or non-verbal reaction of the students by the face-to-face manner, so it is easy to adjust or improve their material to be more understandable. In the e-learning system, by its virtue, the accessible information of the students is extremely limited to the behavioral ones, such as access log, progress log, test record, chatting log, etc. Such statistic information would help to catch responses of students to some extent [1]. However there is still huge gap between them in the manner of collection and evaluation of students' information.

On the other hand a vast of attempts has been made on detecting human mental and somatic states by employing variety of physiological sensors [2,3]. Brain wave (or electroencephalogram; EEG) and heat rate variability (HRV) have been frequently introduced to evaluate human psycho-physiological states, while other bio-electric signals, such as skin temperature [4] and skin conductance (or electrodermal activity; EDA) [5], are recently integrated into the list of physiological measures. Along with this stream of body-mind evaluation researches using integrated physiological measures, however, only a few attempts have been made to investigate such physiological responses of the attendees of e-learning course (e.g., [6,7]). Little is known about what types of materials induce what kind of physiological responses of attendees, while such an objective evaluation enable us to ensure the proper participation of attendees and afford the key to manage the tutor satisfaction in e-learning.

In this study, a novel approach towards the evaluation of students in e-learning sessions is regarded; the physiological responses of the students who were engaged in e-learning materials were investigated. Among a full battery of physiological signals, we focused on human hemodynamic activity, which is represented by the blood pressure. The past hemodynamic studies on mental stress showed that the difference in subject's stress coping style, i.e., active and passive coping, induced different hemodynamic responses [8,9]. Such a variety of stress coping styles is also anticipated to be prevailing in attendees of e-learning course, so it is worth assessing hemodynamic activity of the attendees while learning via e-learning is not always a stressor. In the next the indices of hemodynamic activity and their meanings are briefly described.

II. Hemodynamic Activity and Stress Coping Style

Representative physiological signals in relation to hemodynamic activity are the heart rate (HR), systolic blood pressure (SBP), diastolic blood pressure (DBP), mean blood pressure (MBP), stroke volume (SV), cardiac output (CO), and total peripheral resistance (TPR). HR is the heart beat per minute. SBP and DBP are the highest blood pressures reached when the heart contracts and the minimum blood pressure when the heart relaxes, respectively. MBP is the mean blood pressure during a single cardiac cycle and is approximately obtained by the following formula:

$$MBP \approx DBP + (SBP\text{-}DBP)/3. \quad (1)$$

SV and CO are the volume of blood pumped out from the heart with each beat and that of per minute. CO is thus found by the product of HR and SV;

$$CO = HR \cdot SV. \quad (2)$$

TPR is the blood flow resistance in the body (systemic circulation). It is found in the same manner as Ohm's law for electric resistance;

$$TPR = MBP / CO. \quad (3)$$

These hemodynamic indices are known to increase or decrease according to subjects' stress coping style as shown in Table 1, where "++", "+", "-", "--", and "±" represent each corresponding index, namely always increased, normally increased, normally decreased, always decreased, and unspecific. It should be noted that one cannot discriminate Pattern I and II by only MBP since it shows "++" in both pattern. The hemodynamic response pattern initiated by active coping is named Pattern I, and that by passive coping is named Pattern II [8,9]. The active and passive coping with stressor can be linked to so-called "fight-or-flight" response. Active coping is characterized by fighting against a stressor with practical action or preliminary behavior, whereas passive coping is characterized by bearing the stressor or just keeping watch on the situation. Actually mental arithmetic task and avoidance of electric shock which is a typical laboratory stressor inducing active coping evokes Pattern I response and, by contrast, exposure of noise and unpleasant projected images which induces passive coping evokes Pattern II response [8].

Table 1. Hemodynamic response patterns in active and passive stress coping styles.

	MBP	HR	CO	SV	TPR
Pattern I (active coping)	+ +	+ +	+ +	±	±
Pattern II (passive coping)	+ +	−	−	− −	+ +

In this study we employed these hemodynamic indices to investigate a variety of hemodynamic response against e-learning materials and their relevance with attendees coping style.

III. Method

A. Subjects

Twenty male students aged from 19 to 20 years voluntary participated in this study. They were all domestic technical college students and majoring in information science and technology.

B. Experiment Procedure

The subjects were instructed to attend two e-learning course materials; 1) a lecture on advanced mathematics and 2) a virtual laboratory work on electric circuit. These two course materials were provided by a proprietary e-learning system in our institute (e-learning Higher Education Linkage Project; eHELP), which is one of a largest effectively running e-learning project in our country (See more detail in [10-12]).

The lecture on advanced mathematics was the video recorded material of the ordinary face-to-face lecture in which a university professor delivered a lecture in front of a video camera, so it was characterized by the non-interactive material (herein we name this course material as "*N-IM*"). The other was a virtual laboratory work on electric circuit in which attendees were required to perform a number of given tasks with a terminal PC, so it was characterized by the interactive material (herein we name this course material as "*IM*"). All subjects experienced both *N-IM* and *IM* conditions (within-subjects experiment). Each material took roughly about 25-35 minutes to complete, and a variety of physiological signals described below were assessed in the mean time.

C. Physiological signals

With regard to physiological signals, electrocardiogram (ECG) and blood pressure were recorded by bio-amplifier (BIOPAC MP150 systems, BIOPAC System Inc.) and non-invasive blood pressure measurement system (Finometor, Finapres Medical Systems B.V.), respectively, as shown in Fig.1. These physiological signals were taken continuously in time series at 200Hz of sampling rate.

D. Data Analysis

Since each material took roughly about 25-35 minutes to complete, we analyzed physiological signal of the first 25 minutes for easy comparison. Frequency analysis was performed on ECG data to calculate high frequency (0.15-0.40Hz; HF) power of the signal. HF is considered to represent parasympathetic nervous system activity [13], so it can be taken as an index of subjects' "relax" or "rest". On the other hand, the ratio of HF and low frequency (0.04-0.15Hz; LF) power (LF/HF) has also frequently been referred as an index of "stress" or "concentration", because it was assumed to represent sympathetic nervous system activity [14]. However the recent reviews on related topics concluded that there is no rational reason or mechanical background to take LF/HF as a representation of sympathetic nervous system activity [15], thus it was not taken into data analysis. Other

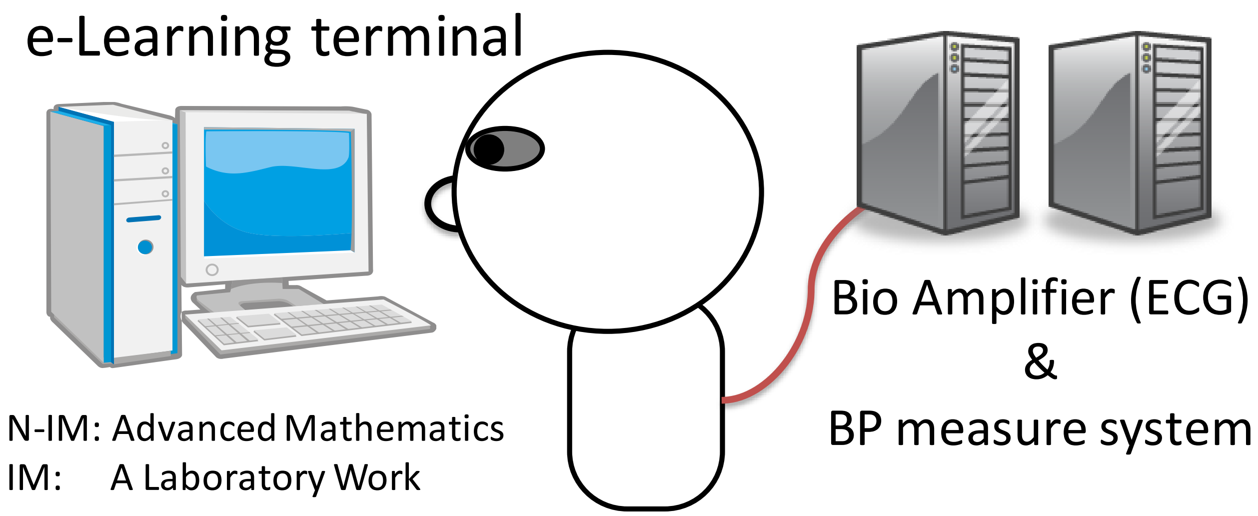

Figure 1. Schema of experiment.

physiological signals in relation to hemodynamic activity, HR, SBP, DBP, MBP, SV, CO, and TPR, were obtained by proprietary software of the blood pressure measurement system (BeatScope, Finapres Medical Systems B.V.).

All these physiological signals were segmented into every 60 seconds and averaged. After that for the better comparison in *N-IM* and *IM* condition of this within-subject experiment, each signal was normalized as follows:

$$z_i = (x_i - x_a) / \sigma. \quad (3)$$

where x_i is an original value (an averaged value of a particular segment), and z_i, x_a, and σ is the normalized value, averaged value, and standard deviation of the original value.

With regard to the statistics, *paired Students t-test* was performed in comparing the difference between the conditions, and *Wilcoxon signed-rand test* was performed in comparing the difference within the condition, e.g., to test a certain values were increased or decreased throughout the experiment period.

IV. Results

A. HF (parasympathetic nervous system activity)

Figure 2(a) shows HF profile in the time series in *N-IM* and *IM* condition, meanwhile Fig. 2(b) represents the average value during the experiment period. It should be noted that, for the better comparison, each trend in Figure 2(a) was baseline corrected by which all data was adjusted so that the initial value in each condition was set to be 0.0. HF remarkably dropped immediately after the e-learning session was started in both condition. This resulted in the significant

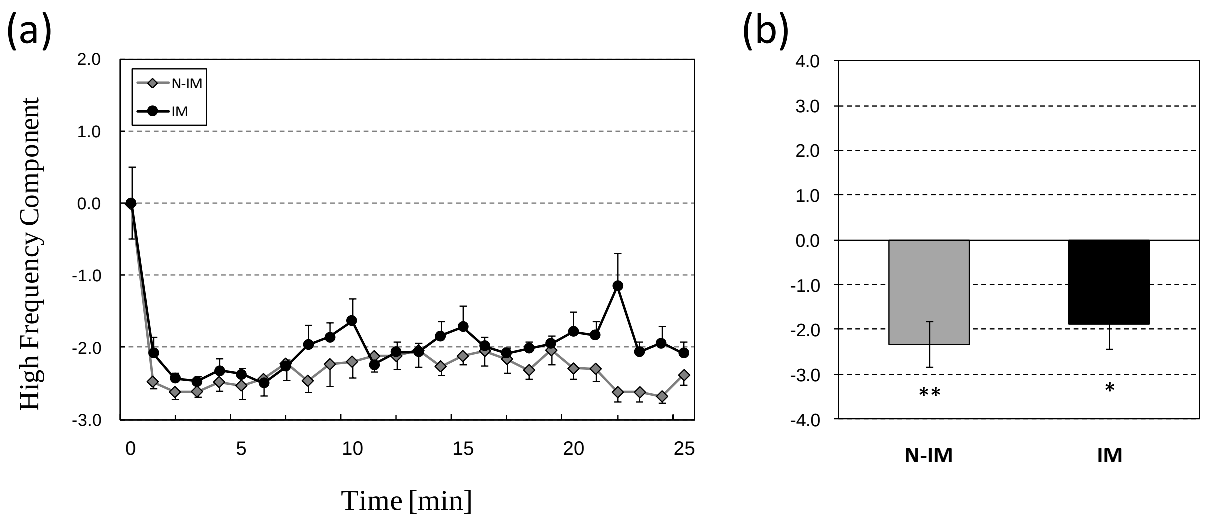

Figure 2. (a) HF profile in the time series and (b) the average during the whole period.

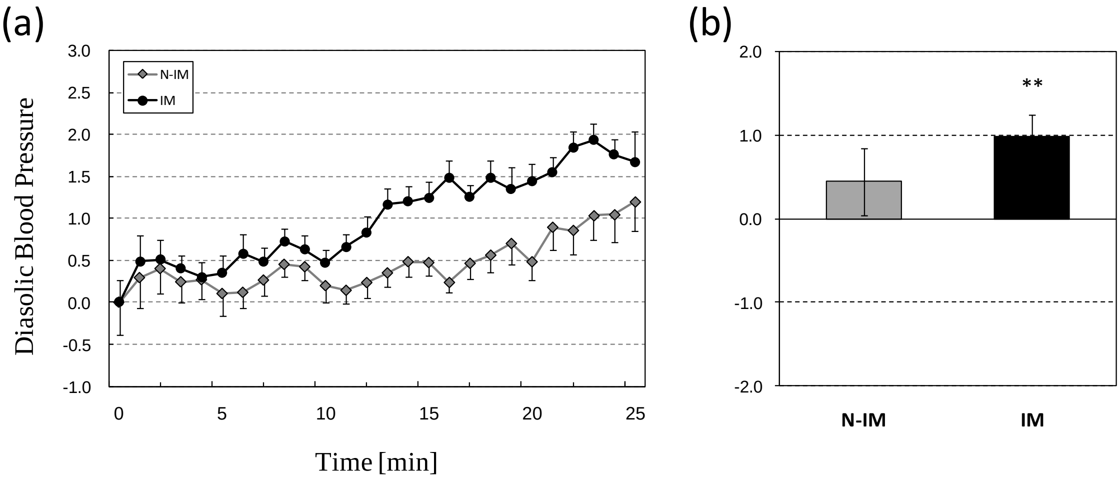

Figure 3. (a) DBP profile in the time series and (b) the average during the whole period.

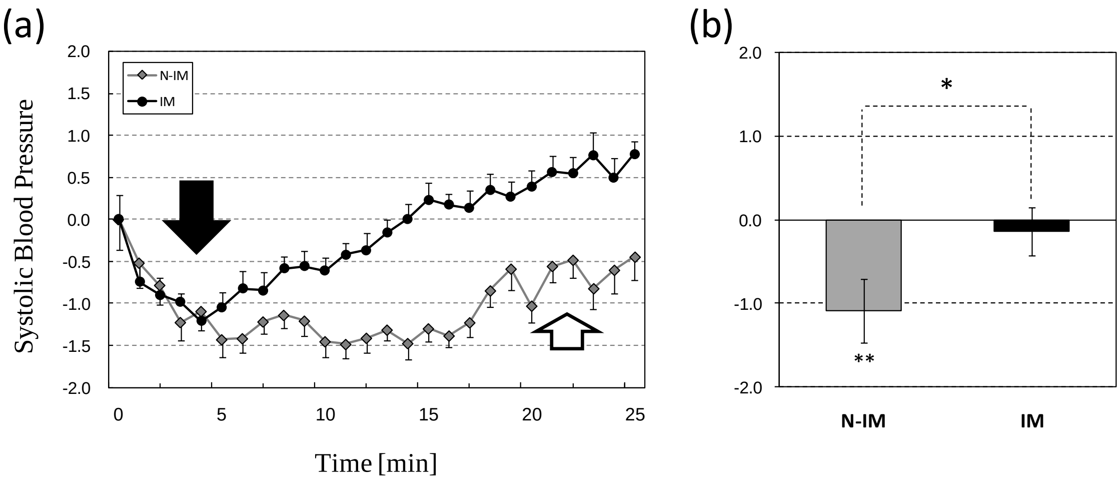

Figure 4. (a) SBP profile in the time series and (b) the average during the whole period.

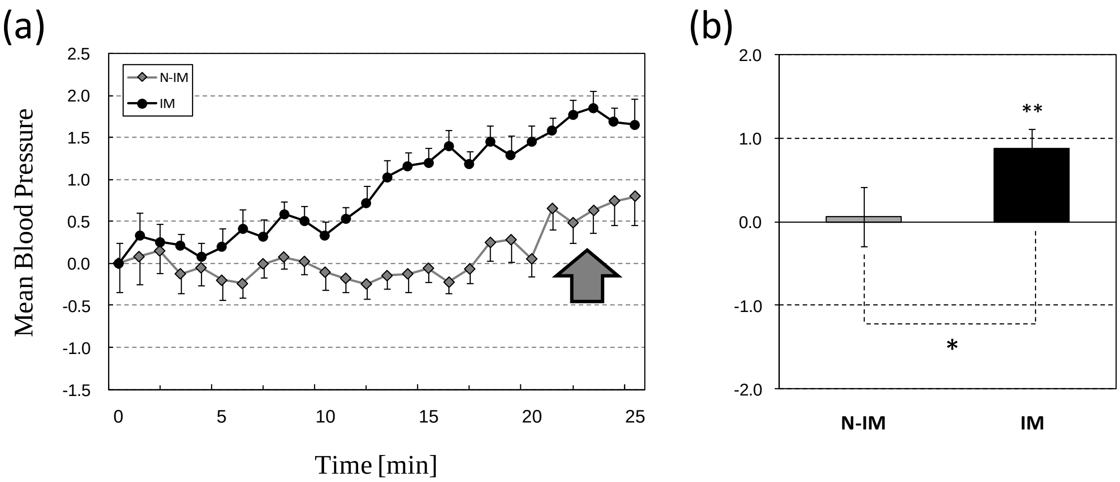

Figure 5. (a) MBP profile in the time series and (b) the average during the whole period.

decline of HF for the whole period in both conditions (p<0.01 for *N-IM* and p<0.05 for *IM*). Since HF can be taken as an index of subjects' "relax" or "rest", it is plausible result; the dropped HF observed in both conditions can be interpreted as the subjects were *not* relaxing or taking a rest. However as a

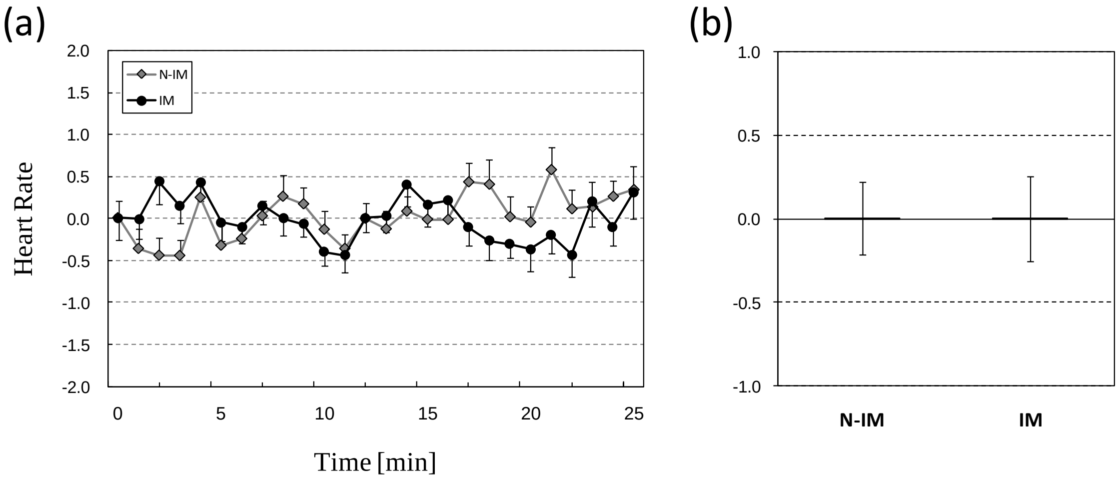

Figure 6. (a) HR profile in the time series and (b) the average during the whole period.

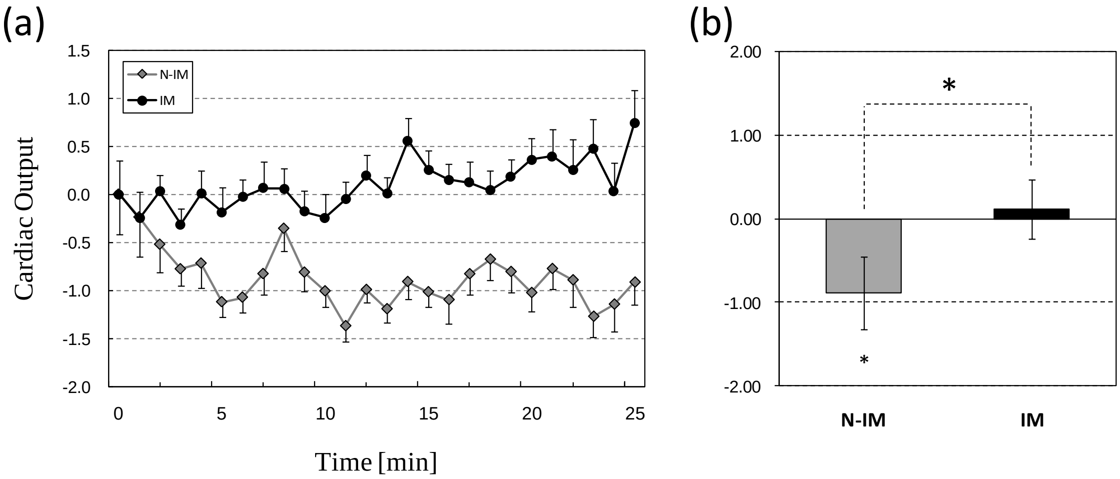

Figure 7. (a) CO profile in the time series and (b) the average during the whole period.

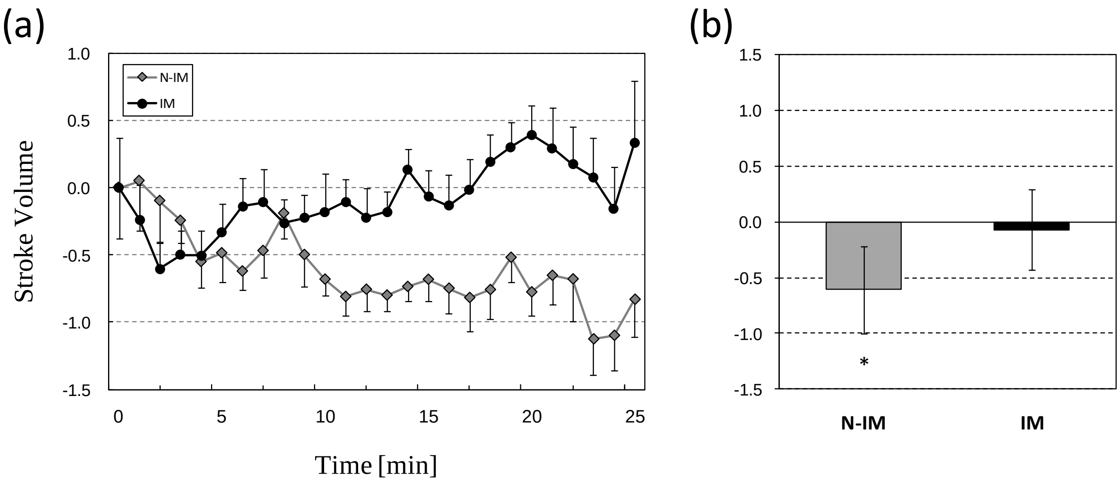

Figure 8. (a) SV profile in the time series and (b) the average during the whole period.

whole there was no significant difference between *N-IM* and *IM* conditions ($p>0.05$).

B. HR, SBP, DBP, MBP, SV, CO, and TPR (Hemodynamic activity)

Fig. 3, Fig. 4, and Fig. 5 shows the time course profile and the average value of DBP, SBP, and MBP as in the same manner

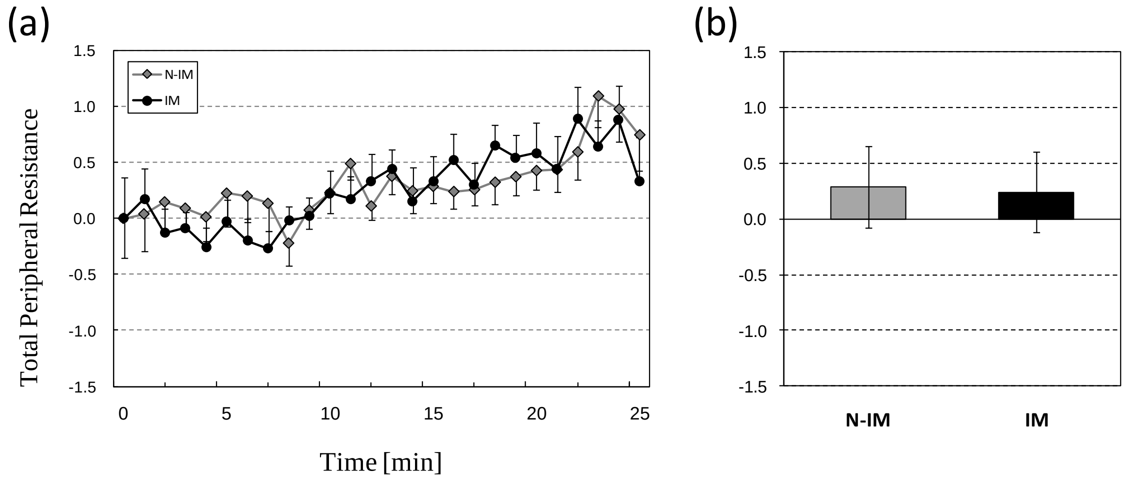

Figure 9. (a) TPR profile in the time series and (b) the average during the whole period.

with Fig. 2. DBP shows a constant increment throughout the experiment period in both *N-IM* and *IM* conditions (Fig.3). The initial decline in the first 5 min was observed in SBP in both conditions (denoted by a black arrow in Fig.4), whereas it gradually recovered afterwards and increased in the end (denoted by a white arrow in the figure). The difference in the speed of recovery in the middle section (5 to 15 min) was observed, and it resulted in the significant difference in the average of the whole experiment period (p<0.05). Since MBP was numerically found by DBP and SBP, the profile of MBP represents both properties. However the increment of MBP was still observed in both conditions while that in *N-IM* was rather slight and delayed increment (denoted by a gray arrow in Fig.5). Fig. 6 shows the result of HR. It did not show any remarkable changes throughout the whole experiment period.

CO and SV showed remarkable differences in *N-IM* and *IM* conditions as shown in Fig. 7 and Fig. 8. SV and CO shows steep increment in *IM* and decline in *N-IM*, and it resulted in a significant difference between conditions in CO (Fig.7 (b): p<0.05). SV and CO showed the most contrasting and remarkable difference in *N-IM* and *IM* conditions among any other physiological signals. Fig. 9 shows the result of TPR. It did not show any significant difference between the conditions, while a slight increment was observed for both conditions.

These hemodynamic responses are summarized in Table 2, where "+", "-", and "±" represents the trends of each profile that observed in a time series. It should be noted that it was denoted with "*" or "**" in case if it were statistically significant at the level of p<0.05 or p<0.01, respectively. Also it was denoted with "#" when it has remarkable profile in the latter half of the experiment. Comparing Table 1 with Table 2, these hemodynamic responses in *N-IM* and *IM* condition is found to be generally corresponding to those in *Pattern II* (passive stress coping) and *Pattern I* (active stress coping); especially in terms of contrasting difference in CO and SV.

V. Discussion

The correspondence in physiological responses in Table 1 and Table 2 that observed in this study are quite unique and intriguing. While such a differentiation in hemodynamic activity against "*stressor*" has been frequently reported in numbers of past psychophysiological studies, all these results were obtained by strictly-controlled *laboratory studies* in which well-designed and relatively acute stressors, such as avoidance of electric shock, cold pressure, mental arithmetic, and other cognitive tasks, are involved [8,9]. On the contrary, so far as we know, no study has ever demonstrated such a difference in hemodynamic responses by a *field study*; the responses observed in our study were not against a distinctive laboratory-controlled stressor but against effectively running e-learning materials. The result in Table 2 is meticulous and is intelligible in this regard. Since the material in *N-IM* condition is a video-recorded ordinary lecture, it can be assumed that such a *non-interactive* activity would induce subject's passive coping by which *Pattern II* hemodynamic responses were initiated in their body. Alternatively in *IM* condition, subjects were required to perform a number of given tasks in the material, so such an *interactive* activity would induce subject's active coping by which *Pattern I* responses were initiated.

HF signal also showed remarkable decline in both *IM* and *N-IM* conditions, as in Fig. 2. However since it can be an index for "relax" and "rest", it would constantly result in

Table 2. Hemodynamic responses observed in IM and N-IM conditions.

	MBP	HR	CO	SV	TPR
IM (interactive)	+**	±	+#	+#	+
N-IM (not interactive)	+#	±	−*	−*	+

"*" and "**" represents statistical significance at the level of p<0.05 or p<0.01, respectively.
#: profiles in the latter half period.

negative value or keep in lower level against *any* e-learning material (Fig. 2), whereas hemodynamic signal, especially SV and CO, would have resulted in contrasting results according to passive or active coping of the subjects. In other words HF can be a practical index to see if the attendees of an e-learning course were not relaxing but concentrating on the material.

The result of this study suggests an idea of anticipation of the "*attitude*" of attendees of e-learning courses. Since the obtained result of this study (Table 2) is a summarized results of all subjects, it is not necessary to consider that all subjects were engaged in the given materials in the same manner. In fact some subjects showed contrasting hemodynamic response among the others; *Pattern II* by *IM* condition and vice versa. Therefore by referring to these hemodynamic activities, it would be possible to anticipate the *attitude* of attendees objectively.

VI. Conclusion

In this study the remarkable difference in the human hemodynamic responses against interactive and non-interactive material in our proprietary e-learning course (eHELP) was observed. Such difference would have been derived by the difference in the *attitude* of the subjects. Although technical and cost limitations for monitoring such physiological signals cannot neglect at this date, it will bring a practical approach to test, improve, and develop e-learning materials in terms of Faculty Development (FD).

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