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Monitoring the Level of Attention by Posture Measurement and EEG

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Abstract

Attention is a factor that affects the performance of various intelligent activities in humans. Up until now, the methods for measuring the level of attention have been mostly based on subjective reports or employing large and costly devices. In this paper, a new method of estimating the level of attention is proposed, based on posture and EEG measurements. These data can be recorded using easily available and less burdensome devices. From the obtained data, the time evolution of attention was explored. Experiments showed that there is negative correlation between posture variance and attention, and also between EEG and attention.

Keywords: attention, posture measurement, EEG

Introduction

Attention is a crucial factor that affects the performance of various intelligent activities in humans. Measuring the level of attention is of a great importance for optimizing the performance. Unless the level is estimated properly, it would not be able to control it. However, most of the ways to monitor the level of attention have been based on participants' reports (Rich & Gureckis, 2015). Although there are methods that uses objective measurement, they required high-cost devices such as fMRI or invasive physiological recordings (Itti & Koch, 2001). In this paper we propose a method of estimating the level of attention using easily available and less burdensome devices. Devices that we used are pressure sensors and a mobile EEG (electroencephalogram) sensor.

Researchers have revealed that there are various types of attention, from a subjective and conscious state of mind to subconscious alert states that can only be measured through psychological tests. In this work, we focus on a subjective and conscious level of attention, which humans can recognize and evaluate by themselves. The goal of this work is to find features in posture and EEG measurement that correlates well with this type of attention.

There are numerous applications realized by monitoring the attentional level. Here we name a few examples in the fields of education, safety management, and cognitive science.

Education: Knowing the level of attention among students is valuable for the lecturer since he can use such feedback for making the lecture more attractive. This is even more important in the case of e-learning, where the lecturer cannot easily see the response of the audience.

Safety management: When an employee has low attention, the monitoring system can warn him or advice the manager for rotation. It is of critical importance since many disastrous incidents were caused by a low level of attention of the worker.

Cognitive science: Monitoring the level of attention is also of interest for cognitive science (Itti & Koch, 2001; Srivastava & Vul, 2016). For example, knowing the time evolution of attention may give a clue to how attention is maintained or generated in the brain.

In these applications, it is preferable to implement a system using easily available devices, in order to make it accessible to a large group of users. The method explored in this work is aimed at realizing such applications.

The underlying assumption of this work is that the posture and EEG of a participant change in correlation to the level of attention. A reason for using posture is that it is a quantity that can be relatively easily measured. Unlike many other physiological quantities, it can also be measured non-invasively. Our preliminary observation showed that the posture of a sitting-down students reflects his/her attention toward the lecture. A focused participant sits fixedly, leaning rather forward. On the other hand, a non-focused participant is likely to change their posture more frequently, often leaning backward. Based on this observation, we propose a hypothesis that the movement of posture reflects the level of attention. This does not mean that a specific posture corresponds to a high or low level of attention. Rather, our model is that indicators such as average or variance of a posture related value correlates with the level of attention. In addition, EEG is known to have correlation with performance in many types of tests (Klimesch, Doppelmayr, Russegger, & Schwaiger, 1998). This indicates that EEG can perform as an indicator for the level of attention. We therefore seek specific indicators in the posture and EEG that are correlated to the level of attention. These indicators are computed from raw signals obtained from sensors.

Related work

Measuring attention

It has been pointed out that attention is limited in time (Nobre & Coull, 2010). Humans cannot sustain a high level of attention for a long period of time. In practice, it is important to know how the level of attention changes over time, and how it can be recovered. This would help making humans more productive. One goal of our work is to uncover such dynamics of attention.

Itti and Koch proposed a model of visual attention that predicts where the participant focuses at (Itti & Koch, 2001). The model was evaluated on the basis of eye movement and object recognition. Srivastava and Vul proposed a new model for the dynamics of attention when a participant is tracking multiple objects displayed on a screen (Srivastava & Vul, 2016). The level of attention was estimated based on how well the participant can judge whether the color of the moving object changed or not, despite many other distracting objects. Walsh et al. evaluated a simulation model for the level of vigilance using the response time of a participant in certain tasks (Walsh, Gunzelmann, & Dongen, 2014).

Sensor measurement

Sensors similar to the ones used in our work have been proposed for estimating the state of a participant while conducting a certain task. Shen et al. used EEG, blood pressure sensor, and perspiration sensor to monitor participants during e-learning (Shen, Wang, & Shen, 2009). Kanki et al. proposed a system for controlling a wheelchair using an array of pressure sensors embedded to its seat (Kanki, Kuwahara, & Morimoto, 2014). The user could direct the wheelchair by moving his center of gravity.

Method

Participants

We tested the system with 17 participants. They were all graduate and undergraduate students in their 20s. Eleven were male and six were female.

Apparatus and stimuli

In our system, the participant's posture is measured using pressure sensors placed within the chair that the participant is sitting on. Using these sensors, the center of gravity of the participant's upper body is tracked. Hereafter, "the center of gravity" refers to that of the upper body of the participant, ignoring the weight supported by their feet. In addition, EEG is measured using a mobile recording device that the participant wears on his/her head. The system and its constituent parts are described in detail in the rest of this section.

Balance board To measure the posture of the participant based on the movement of the center of gravity, we used Nintendo Wii-U balance board[1], illustrated in Figure 1. The board has pressure sensors embedded at four corners, allowing to measure the weight imposed at each corner. Let A, B, C, and D represent four corners of the board, that is, front-left, front-right, back-left, back-right, respectively, as indicated in Figure 2. Let $w_a(t)$ indicate the weight at corner a at time t, where a is for A, B, C, and D. Let $w_\Sigma(t)$ represent the total weight imposed on the board at time t, and s_x and s_y be the width and the depth of the board, respectively. Using the weights at four corners, the horizontal coordinates for the center of gravity $(x(t), y(t))$ can be obtained as follows.

[1] http://www.nintendo.com/wiiu

Figure 1: A chair with a balance board

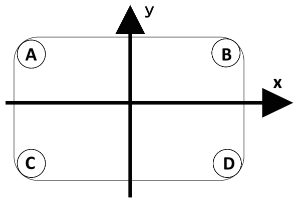

Figure 2: Corners of a balance board

$$
\begin{aligned}
w_x(t) &= w_B(t) + w_D(t) - w_A(t) - w_C(t) && (1)\\
w_y(t) &= w_A(t) + w_B(t) - w_C(t) - w_D(t) && (2)\\
w_\Sigma(t) &= w_A(t) + w_B(t) + w_C(t) + w_D(t) && (3)\\
x(t) &= \frac{s_x}{2}\frac{w_x(t)}{w_\Sigma(t)} && (4)\\
y(t) &= \frac{s_y}{2}\frac{w_y(t)}{w_\Sigma(t)} && (5)
\end{aligned}
$$

The origin of this coordinate system is at the center of the balance board. In other words, $(x(t), y(t)) = (0,0)$ means that at time t the participant's center of gravity has the same horizontal coordinates as the center of the balance board. The size of the balance board used in our experiment was 50 cm by 30 cm, so s_x = 50 cm and s_y = 30 cm. The values of $w_A(t)$, $w_B(t)$, $w_C(t)$ and $w_D(t)$ are recorded from the balance board at 50 Hz, i.e. every 20 milliseconds.

The balance board was placed on a chair whose height was 45.5 cm. The board itself has 5.3 cm height. In total, the height was 50.8 cm, which is close to chairs used in classrooms. Since participants were all graduate and undergraduate students, we considered this total height to be apt. However, the chair had no backrest, which could have made the participant feel less comfortable compared to a regular classroom environment. The height of the table on which the tasks were conducted on was 71.6 cm, which is a little lower than a desk used in a regular classroom.

EEG recording EEG (electroencephalogram) was recorded using Neurosky Mindwave Mobile[2], indicated in Figure 3. Following the recommended usage of the device, electrodes were placed at three sites on the participant's head and forehead, namely Fp1 (frontal pole 1), Fp2 (frontal pole 2), and A1 (auricular 1) recording sites specified by the international 10-20 system. If the participant moves by a large extent during experiments, it can cause some artifacts to EEG recordings. Since such large movements were expected to be prominent for the Reversi task, we placed the game board close to the participant, such that he/she does not need to move his/her arm much.

The power of each frequency band is sampled at 1 Hz. Although various frequency bands are recordable using this de-

[2] http://neurosky.com/

Figure 3: EEG sensing device

Figure 4: Experiment environment

vice, we focused on four bands, namely low α, high α, low β, and high β. Their power at time t is indicated by $\alpha_L(t)$, $\alpha_H(t)$, $\beta_L(t)$, and $\beta_H(t)$, respectively. These are suggested to be most relevant to the level of attention (Klimesch et al., 1998; Yasui, Tian, & Yamauchi, 2008; Yoshida, Sakamoto, Miyaji, & Yamada, 2012). Table 1 shows the frequency for each of these bands, and variables that represent their power.

Table 1: Types of EEG frequency bands

Band	Var.	Frequency	Band	Var.	Frequency
low α	α_L	8∼10 Hz	low β	β_L	12∼20 Hz
high α	α_H	10∼12 Hz	high β	β_H	20∼30 Hz

For estimating the level of attention from the posture of the participant, we propose to use two indicators, namely variances of $x(t)$ and $y(t)$ over time interval I_k. They are based on a hypothesis that when the participant is less focused to the task, they feel more body pain and change the posture more frequently, thus increasing the variance of the center of gravity. For EEG based monitoring, we propose to use the following two variables W and Z that can be calculated from the power of these frequency bands. In the following definitions of $W(t)$ and $Z(t)$, $\alpha_\Sigma(t)$ indicates the total α power and $\beta_\Sigma(t)$ indicates the total β power at time t.

$$\alpha_\Sigma(t) = \alpha_H(t) + \alpha_L(t) \quad (6)$$

$$\beta_\Sigma(t) = \beta_H(t) + \beta_L(t) \quad (7)$$

$$W(t) = \log\left(\frac{\beta_\Sigma(t)}{\alpha_\Sigma(t)}\right) \quad (8)$$

$$Z(t) = \log\left(\frac{\alpha_L(t)}{\alpha_H(t)}\right) \quad (9)$$

W is based on an existing report which states that the strength of the β band is relevant to attention (Yoshida et al., 2012). Z is our own proposal, based on a hypothesis that the composition of the α band is relevant to the level of attention.

Table 2 summarizes the indicators proposed in this paper.

Conditions

Table 3 indicates three types of tasks conducted for each participant. All of the problems were multiple choice problems and were presented by printed documents.

Table 2: Indicators used in the experiments

Indicator	Description
var(x)	The variance of $x(t)$ for all $t \in I_k$.
var(y)	The variance of $y(t)$ for all $t \in I_k$.
mean(W)	The mean of $W(t)$ for all $t \in I_k$.
mean(Z)	The mean of $Z(t)$ for all $t \in I_k$.

Procedure

Figure 4 shows the environment for the experiment. Each participant was asked to sit on top of a balance board placed over a chair. After the outline of the experiment was explained, the participant wears the EEG recording device. The experiment took about one hour for each participant. The participants were divided into two groups. For each group, the three tasks were conducted in the following order.

Group 1 (9 participants): T1 → T3 → T2
Group 2 (8 participants): T2 → T3 → T1

This is to reduce the effect of the participant's level of attention lowering from getting tired from performing many tasks.

We also recorded during resting periods, but since we did not ask the participants to stay still, some of them adjusted the EEG recording device that they were wearing. We are therefore not using data recorded during the resting periods for analysis.

In the Reversi match task, the participants had to play the game under the following constraints.

- For the first three moves, the participant has to wait 10 seconds before making each move.
- After half of all the squares are filled (i.e. 32 squares are filled) with pieces, the sides are abruptly switched, that is, the light side player now plays the dark side and vice versa. This is not told to the participant beforehand.
- Three moves after the switching of the sides, the participant must make each move within 15 seconds after the opponent has made a move.

After these tasks, the participant was requested to fill in a questionnaire after finishing all of the tasks. The questionnaire asks for a subjective description of how his/her level of attention changed as he/she conducted the tasks, scored by an integer from 1 and 5.

Analysis

In the questionnaire, the participants were asked to answer their subjective level of attention by five levels, from "strongly not attentive (1)", "not attentive (2)", "neither attentive nor not attentive (3)", "attentive (4)", and "strongly attentive (5)". Hereafter, we call each of the level as a class.

Table 3: Types of tasks

ID	Task	Description	Time intervals
T1	CAB calculation problems	10 minutes time limit. 27 mental computation problems, 18 arithmetic calculation problems, and 18 geometric problems.	$I_1 \sim I_3$
T2	GAB word problems	10 minutes time limit. 24 problems from 8 documents.	$I_4 \sim I_6$
T3	Reversi match	1 game, which takes about 15 minutes.	I_7, I_8

Tasks T1 and T2 were divided into three equal-sized intervals, and T3 was divided into two equal-sized intervals. These eight time intervals are represented by $I_1, I_2, ..., I_8$, which are defined in Table 3. Each participant had to give five-level grading for his/her level of attention during each of the time intervals. As a result, an 8-dimensional vector $C^{(i)}$ is obtained for each participant i. Its k-th component $C_k^{(i)}$ is the subjective level of attention at interval I_k for participant i , where $k \in (1,2,...,8)$

Let X represent any of four indicators, i.e. var(x), var(y), mean(W), and mean(Z). For X of participant i, we get an 8-dimensional vector $\overline{X}^{(i)}$, whose k-th component $\overline{X}_k^{(i)}$ is obtained by time averaging $X^{(i)}(t)$ over time intervals I_k. $|I_k|$ represents the number of sampling time points in I_k.

$$\overline{X}_k^{(i)} = \frac{1}{|I_k|} \sum_{t \in I_k} X^{(i)}(t) \tag{10}$$

We evaluated the indicators based on how well they correlate with the subjective level of attention. For example, Pearson's correlation coefficient between indicator $\overline{X}^{(i)}$ and the subjective level of attention $C^{(i)}$ is computed for each participant i as follows.

$$R_{(X)}^{(i)} = R(\overline{X}^{(i)}, C^{(i)}) \tag{11}$$

When there are N participants, the average of Pearson's correlation coefficient for indicator X is computed as follows.

$$R_{(X)} = \frac{1}{N} \sum_{i=1}^{N} R_{(X)}^{(i)} \tag{12}$$

Results

Questionnaire

Table 4 summarizes the answers of the participants to the questionnaire. Each row represents a participant, and a column is a time intervals defined in Table 3. Figure 5 shows the distribution of the answers. A box represent the 25th and 75th percentiles, and a red plus is an outlier. The plot shows that for the CAB calculation problem task and the GAB word problem task, there is a tendency that reported levels of attention decreases as the time passes.

Table 4: Participants' answers to the questionnaire

	T1			T2			T3	
participant	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8
P1	5	2	2	5	2	2	1	2
P2	4	5	4	5	4	5	1	4
P3	4	3	2	3	1	1	1	2
P4	4	3	3	5	5	5	5	5
P5	5	5	4	5	3	3	5	5
P6	1	2	2	4	4	4	1	4
P7	3	4	5	2	2	3	5	5
P8	2	2	2	4	4	4	1	1
P9	5	4	2	5	5	4	1	4
P10	4	4	5	3	4	5	5	5
P11	5	5	4	5	5	3	5	4
P12	4	5	4	5	4	4	5	5
P13	5	4	4	4	5	4	5	2
P14	4	5	1	2	4	1	5	2
P15	4	3	4	4	4	3	5	5
P16	4	4	2	5	4	4	1	5
P17	5	4	4	5	4	4	5	4

Dynamics

Figures 6, 7, and 8 indicate the center of gravity for 5 different participants (Participants 1 $\sim$ 5) at different time points, sampled at 1 Hz, during three different types of tasks (T1$\sim$T3). Participants can be distinguished by marker types. Note that the x-axis is more stretched than the y-axis. The plot shows that the distributions of the center of gravity vary among participants. Some participants have wider distribution, indicating they tend to move more during the task, while others are more fixed, having smaller variance. It can also be seen that for the Reversi match task (T3), the participants are more likely to change their center of gravity.

Figures 9, 10, 11, and 12 show the time evolution of the indicators for Participants 1 $\sim$ 4 during the CAB calculation problem task. Time is indicated in seconds.

Correlation

Table 5 summarizes the correlation coefficients between the subjective level of attention and different indicators. For var(x), may participants show negative correlation with the subjective level of attention, suggesting that when the participant is less attentive, he/she tends to change his/her posture either more frequently or widely to the x direction (sideways), thus increasing the variance. For the column for var(x) and

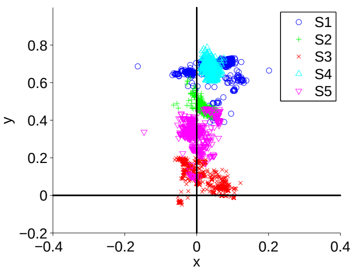

Figure 6: The center of gravity for the calculation task

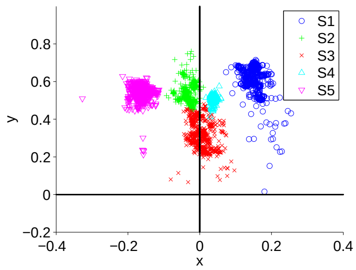

Figure 7: The center of gravity for the word problem task

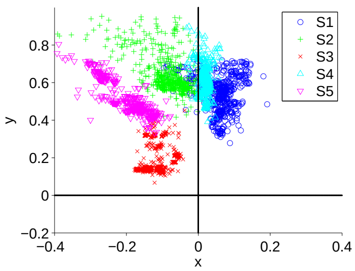

Figure 8: The center of gravity for the Reversi match task

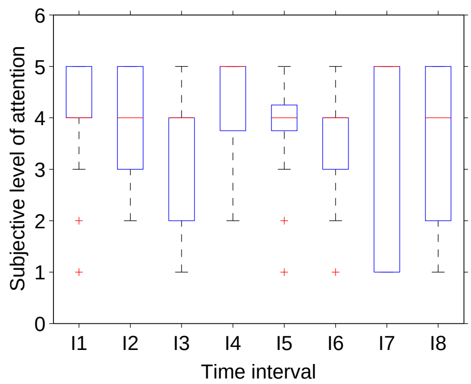

Figure 5: Subjective levels of attention by time intervals

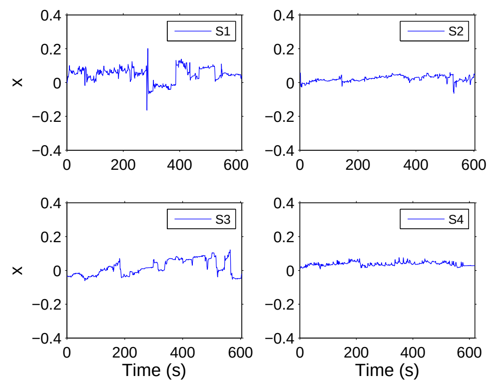

Figure 9: Time evolution of $x(t)$

var(y), cells with negative correlation are emphasized. On the other hand, mean(W) and mean(Z) had positive correlation with the subjective level of attention for many participants, but the difference is not significant. For these columns, cells with positive correlation are emphasized. Since EEG requires intensive preprocessing such as filtering. We are expecting that adding such preprocessing may improve the result. Although the correlation coefficients were of moderate quantity at this moment, we expect that combining these indicators would enable good estimation of the level of attention. Such extension would require determining optimal weight coefficients for combining these indicators. This is left to future work.

Conclusion

A method of estimating the level of attention using posture measurement and EEG was proposed. The posture and EEG of the participants were successfully measured using easily available and less burdensome devices.

The measured attentional level was based on retrospective reports from the participants, which could be inaccurate. We would like to introduce more objective measures of attention which could be measured in real-time. In addition, we plan to measure the lower body of the participants, especially leg positions, using an infrared sensor placed under the table.

In future work, we would like to develop an estimation method for the level of attention by combining the indicators discussed in this paper. Machine learning algorithms can be used to combine the indicators such that it estimates the actual level of attention well. We also plan to search for specific patterns that would appear when the level of attention changes. For example, in Figures 9 and 10, Participant 1 shows abrupt change of $x(t)$ at around 300 seconds (5 minutes) and that of $y(t)$ at around 550 seconds (9 minutes) after the start of the task. This could be due to some disruption of attention. Rather than looking at the average value of the indicator over a time interval ranging a few hundreds of seconds, we plan to look at local features that indicate some change in the level of attention.

Acknowledgments

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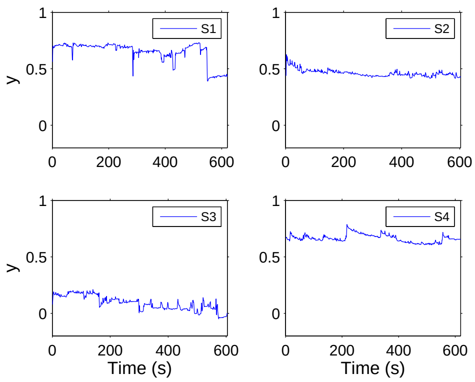

Figure 10: Time evolution of $y(t)$

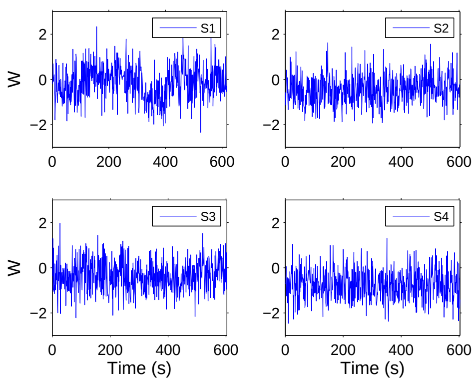

Figure 11: Time evolution of $W(t) = \log\left(\frac{\beta_\Sigma(t)}{\alpha_\Sigma(t)}\right)$

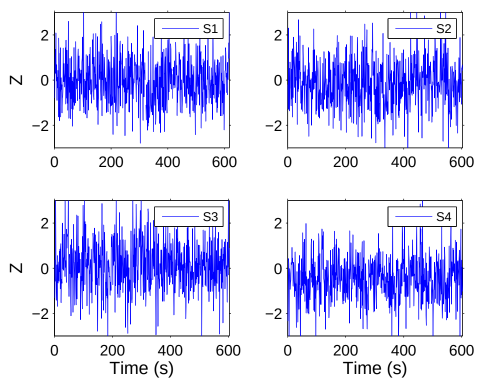

Figure 12: Time evolution of $Z(t) = \log\left(\frac{\alpha_L(t)}{\alpha_H(t)}\right)$

Table 5: Pearson's correlation coefficient between the indicators and the subjective level of attention

Participant	**var(x)**	**var(y)**	**mean(W)**	**mean(Z)**
P1	**-0.3582**	**-0.5319**	**0.4696**	**0.0638**
P2	**-0.8404**	**-0.5287**	-0.3096	-0.0243
P3	**-0.0571**	**-0.4817**	-0.3967	**0.0506**
P4	**-0.0391**	0.3090	**0.5100**	**0.3829**
P5	0.4570	0.6397	-0.7074	-0.2620
P6	**-0.3074**	**-0.4317**	**0.6861**	**0.5125**
P7	0.7891	0.6442	**0.0053**	-0.5354
P8	**-0.7207**	**-0.5835**	**0.5780**	**0.4819**
P9	**-0.5879**	**-0.3808**	**0.3891**	**0.4651**
P10	**-0.1183**	**-0.0600**	-0.1748	-0.1248
P11	**-0.0176**	**-0.3879**	**0.6273**	-0.2381
P12	0.1826	0.4798	-0.5971	-0.3259
P13	**-0.2274**	**-0.5233**	**0.4781**	**0.1991**
P14	**-0.0403**	0.4332	-0.3212	**0.0670**
P15	0.6796	0.8574	**0.2897**	**0.2070**
P16	**-0.3865**	**-0.4959**	**0.3135**	**0.4759**
P17	**-0.0190**	**-0.1357**	-0.3908	-0.1482

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