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Predicting Attention and Memory Ability based on the Combination of EEG and HRV data in Children

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뇌파와 심박수 조합을 바탕으로 한 아동의 집중력 기억력 예측

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<ABSTRACT>

Good performance is important element not only in workplace but also in daily activities. Performance of the human depends on the mental capacity and mental workload. Especially, children in concrete operational stage is critical for further learning ability that they develop their ability to distinguish between quality and quantity. However, the reason that mental workload is difficult to quantify through physiological measures, makes it more complicated to demonstrate the mental workload. When it comes to children’s development, physical change is visible and easy to identify but mental change is not. HRV is relatively easy to measure but has limitation because it is indirect way of measuring brain signal. Above all things, many researches of real-time indicator measuring physiological data such as heart rate variability (HRV) have been done sporadically but not integrated. Therefore, In this study we tried to demonstrate if we can predict the mental capacity not mental workload with the EEG. Attention ability was measured with Stroop task, and memory ability was measured with digit span task. The main outcome of this study is that building predictive models for cognitive functions using physiological measures is feasible and that its predictive models for cognitive functions using physiological measures is feasible and that its predictive power is further improved when EEG is used along with HRV data. It is implied form the outcome of study that combining physiological measures may improve its predictive power by improving the signal relative to noises and that future studies may focus on discovery of further biomarkers for prediction of cognitive functions.

Key words : Physiological data, EEG, HRV, attention ability, memory ability, algorithms formula

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I. Introduction

Good performance is regarded as important element not only in workplace but also in daily activities(Dornhege, 2007). Performance of the human depends on the mental capacity and mental workload. Therefore, performance of human decreases under the higher mental workload compared to their mental capacity (Wang et al., 2012). Skin conductance response (SCR), breath rate (BR), heart rate variability (HRV), and electroencephalography (EEG) are related to activation in sympathetic nervous system. If human operator is affected by mental health such as stress, it activates sympathetic nervous system. It affects regulating functions such as Breath rate, heart rate (HR), heart rate variability (HRV) and electroencephalography (EEG) (Waterhouse & Campbell, 2014). Many researchers use physiological data as real-time indicator to measure the mental workload compared to currently given task and mental capacity (Sejnowski et al., 2007). Another research using physiological data shows that increase in cognitive workload activates sympathetic nerve system and inactivates para-sympathetic nervous system (Cinaz et al., 2013) This means that increase in cognitive workload physiological measures changes until it reaches plateau (Dornhege, 2007). For integrated understanding of brain based cognition and behavior, multi-disciplinary researches using electroencephalography (EEG) is being developed (Kramer & Parasuraman, 2007; Parasuraman, 2003). EEG shows accurate changes in signals regarding alertness, attention and workload. Changes can be identified and quantified with this tool depending on time. There are many researches demonstrating high correlation between changes in cognitive status and EEG indices under many circumstances such as workplace, stimulation (Berka et al., 2004; Brookhuis & Waard 1993; Gevins et al., 1997; Makeig & Jung, 1996; Sterman & Mann, 1995). The EEG PSD (Power Spectral Density) bands or ERP component measurements were used as inputs to classifier models for allowance of identification and classification of cognitive signals such as mental workload, engagement, executive function, attention and memory ability. When it comes to Heart rate variability (HRV), it has been researched as important marker of autonomic nervous system (ANS) (Sandercock, 2007; Pagani et al., 1997; Achten & Jeukendrup, 2003). ANS is composed of parasympathetic nervous system (PNS) and sympathetic nervous system (SNS). (Thayer & Brosschot, 2005) SNS attenuation and PNS activation is related to high HRV, especially it is associated with high frequency component (HF) and higher prefrontal cortex (PFC) (Thayer & Lane, 2009). Based on this, researches regarding HRV and cognitive performance were conducted (Hansen & Johnsen et al., 2003; Hansen et al., 2007). Participants with high HRV showed higher performance on executive tasks compared to participants with low HRV (Thayer & Lane, 2006).

Nowadays, more and more people try to maintain their health and prevent illness, and also they try to promote their quality of life with various options. Likewise, in the healthcare area, physiological data have many benefits. However, it has many limitation to be used in daily life. EEG is rarely used outside of hospitals, and it has problem of high noise when collecting brain signals if used in daily life which means inaccurate and less effective (Sweeney et al., 2012). Also, ordinary people lack professional information to use EEG (Berka et al., 2007). Heart rate variability has advantages of simple measuring process. However, isolated HRV measurements have low sensitivity and low positive predictive accuracy. As a univariate predictor, HRV has low sensitivity and low positive predictive accuracy. Moreover, there is limitation quantifying mental capacity and workload by physiological measures. Piaget's cognitive development theory is a theory about human intelligence specially developmental stage (Reynolds & Fletcher-Janzen, 2007). Piaget's theory of cognitive development is composed of 4 stages which is sensorimotor, preoperational, concrete operational and formal operational period. Piaget demonstrated that childhood is crucial and important period regarding lifelong development of human.

This study aims attention and memory ability of children who are in Concrete operational stage. They have to develop attention and memory skills which is important for learning task. The hypothesis of this study is to develop a prediction model which can predicts the children's attention and memory ability based on EEG brain region and brainwave. In addition, another physiological tool, HRV was added to the model to develop more accurate prediction model of attention and memory ability. The purpose of this study is to combine physiological tools to makeup the limitations of its own if used separately, and based on this, We suggests framework to simply predict children's attention and memory ability. Combined physiological data framework can provide real-time prediction of current attention and memory ability and its maximum capacity to simply check these. EEG and HRV were used to measure the physiological data and tasks of attention and memory ability were used to measure the mental capacity performance.

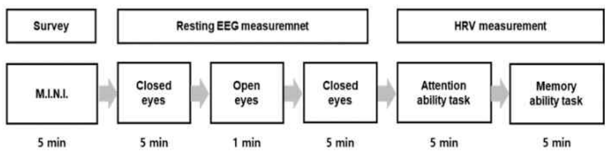
II. Methodology

1. Participants

Fifty, right-handed elementary school students (22 females, 28 males, ages: 6-12) participated in the study for two month. All subjects and their parents provided informed consent before participating, and the study was approved by the Institutional Review Board (IRB # 1703-001-002) at Seoul National University, Korea. The participants with BMI over 23 was excluded from the study and participants with the symptoms of ADHD whose attention is expected to be impaired were also excluded from participating to this study in the screening phase. Any food intake was prohibited from 2 hours before the experiment for the safety of the participants.

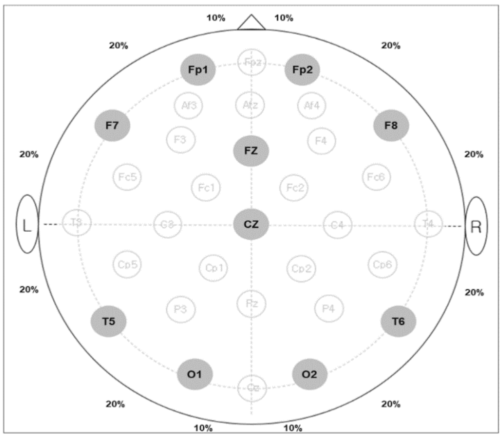
2. Procedure

In a quiet laboratory room, each participant was instructed to sit on a comfortable armchair. Participants were instructed about the procedure of the experiment (fig. 1). EEG was acquired using (Neuromedi EEG, KOR) and HRV was acquired using EDA100C (Biopac Systems Inc, CA, USA).



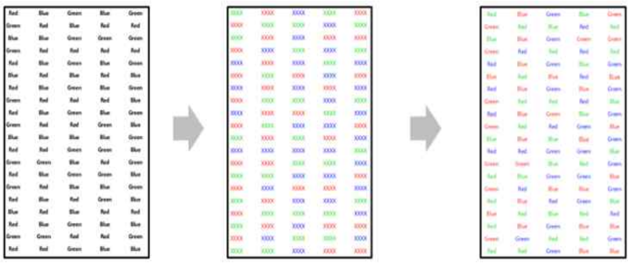
[Figure 1] Entire procedure of the experiment

Mini international neuropsychiatric interview (M.I.N.I) were conducted to the participants and their accompanied parents for 5 minutes. And then, total 10 electrodes were placed on participant's brain according to 10-20% international standard system (fig. 2). Resting EEG were measured for 11 minutes. As the experiment starts, participants closed their eyes and remained resting state for 5 minutes. And they open their eyes and rests for 1 minutes and then, closed their eyes again and remained resting state for 5 minutes again. Electrodes measuring heart rate variability were placed on back of both hands and right ankle.



[Figure 2] Location of 10 electrodes based on 10/20 system

For 10 minutes. 3 stages of Stroop task were conducted to measure attention ability performance (fig. 3). After Stroop task, 2 stages of digit span task were conducted (forward and backward) to measure memory ability performance (fig. 4). When HRV measurement ended, all the electrodes were removed and the experiment was completed.



[Figure 3] Procedure of the Stroop task

	Forward memory task		Backward memory task
(1)	3 · 8 · 6	(1)	2 · 5
	6 · 1 · 2		6 · 3
(2)	3 · 4 · 1 · 7	(2)	5 · 7 · 4
	6 · 1 · 5 · 8		2 · 5 · 9
(3)	8 · 4 · 2 · 3 · 9	(3)	7 · 2 · 9 · 6
	5 · 2 · 1 · 8 · 6		8 · 4 · 9 · 3
(4)	3 · 8 · 9 · 1 · 7 · 4	(4)	4 · 1 · 3 · 5 · 7
	7 · 9 · 6 · 4 · 8 · 3		9 · 7 · 8 · 5 · 2
(5)	5 · 1 · 7 · 4 · 2 · 3 · 8	(5)	1 · 6 · 5 · 2 · 9 · 8
	9 · 8 · 5 · 2 · 1 · 6 · 3		3 · 6 · 7 · 1 · 9 · 4
(6)	1 · 6 · 4 · 5 · 9 · 7 · 6 · 3	(6)	8 · 5 · 9 · 2 · 3 · 4 · 2
	2 · 9 · 7 · 6 · 3 · 1 · 5 · 4		4 · 5 · 7 · 9 · 2 · 8 · 1
(7)	5 · 3 · 8 · 7 · 1 · 2 · 4 · 6 · 9	(7)	6 · 9 · 1 · 6 · 3 · 2 · 5 · 8
	4 · 2 · 6 · 9 · 1 · 7 · 8 · 3 · 5		3 · 1 · 7 · 9 · 5 · 4 · 8 · 2

[Figure 4] Numbers used for digit span tasks

3. Data Analysis

EEG data, HRV data, and the scores of the tasks of 50 participants were analyzed. EEG data and HRV data were used as independent variable. Attention and memory task score were used as dependent variables. In the further analysis with EEG, electrode T6 was excluded from the analysis. HRV data of 36 participants were analyzed. Rest of data were eliminated because of measuring error. 2 ways of analyzing tools were used to demonstrate the correlation of EEG, HRV and attention. First, multiple regression was conducted depending on brainwaves (alpha, beta, gamma, delta, theta). To examine if the model is available F examination were conducted under 0.05 significance. In the model which is significantly meaningful, comparison of R2(adjustedR2) were conducted. ANOVA was conducted to analyze the significance of variables. With the same analyzing tools, correlation of EEG, HRV, and memory tasks were analyzed with multi-regression test and significance of variables were also examined (Tibshirani, R., 1996).

III. Results and Discussions

1. Most predictable attention and memory ability algorithm model based on ROI (EEG) analysis

Among the electrodes which was placed two per each area, we tried to figure out which area most accurately predicts attention and memory ability. Stroop task was used to measure selective attention ability (fig. 3: t-score of step2-step3). In this study used Digit span task to measure working memory capacity (fig. 4. t-score of forward + backward).

2. Right frontal (F8) is the one of predictable attention ability algorithm model and Addition of HRV data to attention ability algorithm model increases prediction accuracy.

F8 electrode in right frontal area was proved to be significant model (p<0.05) (R2=0.2814, p<0.0210) (fig. 5A). Attention ability prediction algorithms formula is Attention ability score = 49.78965 - 0.02776*(F8, ß) + 0.07511*(F8, δ) - 0.08827*(F8, ɣ) + 0.81112*(F8, Θ). With the previous model, HRV data (Sympathetic-vagal balance) were added and analyzed again to check the correlation with the attention ability. F8 electrode in right frontal area was proved to be significant model (p<0.05) and the added data increased the accuracy of the model. (R2=0.2814 → 0.3175, p<0.0210 → 0.0403) (fig. 5B). Attention ability prediction algorithms formula is Attention ability score = 24.1488 + 0.1901*(F8, ß) + 0.3024*(F8, δ) + 0.1465*(F8, ɣ) + 1.0506*(F8, Θ) + 1.8506*(HRV).

A

Electrodes	P-value	R-squred
Fp1	0.2896	0.1327
Fp2	0.3168	0.1263
O1	0.3415	0.1209
O2	0.8919	0.03137
F7	0.4727	0.0961
F8	**0.0210**	**0.2814**
T5	0.3770	0.1137
FZ	0.1479	0.1763
CZ	0.4901	0.0931

B

Electrodes	P-value	R-squred
Fp1	0.0961	0.2644
Fp2	0.2226	0.2047
O1	0.494	0.1344
O2	0.7729	0.0795
F7	0.4606	0.1415
F8	**0.0403**	**0.3175**
T5	0.4374	0.1466
FZ	0.1481	0.2349
CZ	0.4987	0.1334

[Figure 5] Multi-regression analysis based on brain regions. (A) When using only EEG data, F8 electrode in right frontal area was proved to be significant model (R2=0.2814,p<0.0210). (B) When the HRV data were added to the previous analysis, added data increased the accuracy of the model. (R2=0.2814→0.3175,p<0.0210→0.0403).

3. Occipital (O2) is the one of predictable memory ability algorithm model and Addition of HRV data to memory ability algorithm model increases prediction accuracy.

Forward digit span task is related to working memory ability especially backward digit span task is related to working memory especially central executive system (GrÉGoire & Van der Linden, 1997). O2 electrode in occipital area was proved to be significant model (p<0.05) (R2=0.3069, p<0.0122) (fig. 6A). Memory ability prediction algorithms formula is memory ability score = -11.28313 + 0.18673*(O2, ß) + 0.77447*(O2, δ) + 0.24961*(O2, ɣ) + 1.88056*(O2, Θ). With the previous model, HRV data (Sympathetic-vagal balance) were added and analyzed again to check the correlation with the memory ability. O2 electrode in occipital area was proved to be significant model (p<0.05) and added data increased the accuracy of the model. (R2=0.3069 → 0.4481, p<0.0122→ 0.0028) (fig. 6B). Memory ability prediction algorithms formula is memory ability score = -9.59049 + 0.16593*(O2, ß) + 0.75304*(O2, δ) + 0.16499*(O2, ɣ) + 1.81548*(O2, Θ) + 0.60024*(HRV).

A

Electrodes	P-value	R-squred
Fp1	0.2078	0.1549
Fp2	0.1429	0.1784
O1	0.1579	0.1723
O2	**0.0122**	**0.3069**
F7	0.7579	0.0523
F8	0.4431	0.1013
T5	0.1696	0.1678
FZ	0.7927	0.0471
CZ	0.6878	0.0626

B

Electrodes	P-value	R-squred
Fp1	0.2720	0.1887
Fp2	0.1659	0.2268
O1	0.1142	0.2529
O2	**0.0028**	**0.4481**
F7	0.9420	0.0395
F8	0.6352	0.1063
T5	0.3083	0.1783
FZ	0.7173	0.0904
CZ	0.6826	0.0971

[Figure 6] Multi-regression analysis based on brain regions (A) When using only EEG data, O2 electrode in occipital area was proved to be significant model (R2=0.3069,p<0.0122). (B) When the HRV data were added to the previous analysis, added data increased the accuracy of the model. (R2=0.3069→0.4481,p<0.0122→0.0028).

In this study, we aimed to develop simple framework which can predict attention and memory ability mostly with the brain area which was measured with EEG. Analyzing several brain areas and brainwaves at the same time, we found out the most predictable variables. However, since we did not analyze each variable separately and there are many other factors that affect cognitive functions, the resulting prediction of cognition should not be solely attributed to physiological variables. Also Another limitation of this study includes that the electrode T6 was excluded from the analysis due to technical issues and not all electrode sites were recorded and it may limit the interpretation of the results. So it is not yet to be concluded to physiological phenomenon. We tried to demonstrate the predictive power of physiological variables including EEG and HRV to predict cognitive functions including memory and attention (De Los Reyes et al., 2013). However, since we did not analyze each variable separately and there are many other factors that affect cognitive functions, the resulting prediction of cognition should not be solely attributed to physiological variables. This study aimed to develop a simple and clinically useful framework by selecting the most meaningful information predicting attention and memory function from physiological data (Berka et al., 2007). Therefore, the results and frameworks from this study may contribute to help people to simply use physiological data as real-time indicators without professional knowledge. Future studies might be conducted in other age groups including adults and elderly people to develop models predicting cognitive function using physiological variables. Systems which help interaction between people and technologies boost productivities and qualities of daily life, workplace, and in educational settings (Marois & Ivanoff, 2005). However, there are several limitations that should be considered to achieve such a goal. First, we have to define measuring tool which can steadily work. Second, we have to increase the number of participants to increase the accuracy of prediction. Also, with the combination of other physiological measurement (ex> SCR, BR), ultimately we have to develop the integrated physiological measurement framework for mental health assessment. Lastly, Framework of this study needs compatibility with physiological measurement for selection of user's physiological raw data. Additional UX/UI applications are needed to be easily used in daily life. There are previous studies that physiological data are used as meaningful clinical information for clinical applications. However, there are no combination between technologies for ordinary people compared to technical improvement (De Los Reyes & Aldao, 2015). Ordinary people need the system which can trach their maximum mental capacity and manage it. For this, index (mental state gauge) is needed as real-time indicator. It will increase the quality of daily life (Gurses et al., 2009). This is pilot study which is for people who eager to manage their proper health state to measure and analyze their state.

IV. Conclusions and Implications

The main outcome of this study is that building predictive models for cognitive functions using physiological measures is feasible and that its predictive power is further improved when EEG is used along with HRV data. It is implied from the outcome of study that combining physiological measures may improve its predictive power by improving the signal relative to noises and that future studies may focus on discovery of further biomarkers for prediction of cognitive functions.

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