Labelling Method by Pupillometry for Classifying Attention Level by EEG/ECG/NIRS

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Labelling Method by Pupillometry for Classifying Attention Level by EEG-ECG-NIRS

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Abstract

There are numerous methods to evaluate attention levels such as observation, self-assessment, and objective performance. This study aims to propose a new labeling method for attention levels detection by using parameter settings of pupillometry. This parameter setting then would be applied as data labeling in supervised machine learning toward EEG-ECG-NIRS.

To develop parameter settings of attention level evaluation, this study investigated the reaction of blink rates and pupillometry toward attention level based on self-assessment during cognitive tasks. My result showed there is no significant differences ($P>0.05$) in blink rates toward attention level within 10 seconds. On the other hand, pupillometry in low attention showed significant differences in pupillometry in the last 4 seconds cognitive tasks ($P<0.05$). After that, I calculated the distribution fit of pupillometry reaction in the attention level of all participants and plot the critical point of pupillometry data in 10 seconds and 4 seconds. After doing several experimental procedures, I chose parameter setting with a percentage of error of less than 15% and a different error 35 % compare with self assesment as future labeling method. Parameter setting which has been selected is when z-score within a specific range ($-0.965 \leq \text{pupil} \leq 1.014$) as high attention, other that range, will be classified as low attention.

Furthermore, I applied my labeling method for another physiological signal such as electroencephalograph (EEG), electrocardiograph (ECG), and near-infrared spectroscopy (NIRS). Numerous methods using electroencephalograph (EEG), electrocardiograph (ECG), and near-infrared spectroscopy (NIRS) for attention level detection have been proposed.

However, the results were either unsatisfactory or required many channels. In this study, I introduce the implementation of an EEG-ECG-NIRS for attention level detection. I used two-electrode wireless EEG, a wireless ECG, and two wireless channels NIRS to detect attention level during backward digit span, forward digit span and arithmetic. High attention will be labelled to data which has pupillometry z-score within specific range ($-0.965 \leq$ pupil ≤ 1.014) and another that range, will be classified as low attention. By using CFS+kNN algorithm, my result showed the accuracy system of EEG-ECG-NIRS (83.33± 5.95%) has the highest accuracy compare with EEG (81.90± 4.69%), ECG (82.51±3.57%), NIRS (78.37±7.12%). Algorithm CFS+kNN also shown highest performance compare with other methods such as CFS+SVM (55.49± 27.89%), kNN (80.84± 3.88%) and SVM (55.88± 13.14%)

In summary, in this study, I established new parameter settings for evaluating attention level by using pupillometry and apply the parameter settings into EEG-ECG-NIRS to evaluate the EEG-ECG-NIRS performance, comparing with standalone system.

Keywords: labeling, supervised machine learning, blink rates, pupillometry, electroencephalograph, electrocardiograph, near-infrared spectroscopy, attention level detection

Ethics statement

The protocols for the present study were designed in accordance with the Declaration of Helshinki and were approved by faculty of information science and electrical engineering, Kyushu University (H26–3). Informed consent was obtained in writing from each participant

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Chapter 1. General Introduction

Attention can be defined as the processing or selection of information at the expense of other information (Phashler et al., 1998; Anderson et al., 2004; Fougnie. 2008). Similarly, in 1890 psychologists and philosophers William James defines attention as taking possession by the mind, in clear and vivid form, of one out of what may seem several simultaneously possible objects or trains of thought. This implies withdrawal from some things to deal effectively with others (James. 1890). Attention also has been a key cognitive mechanism of interest in terms of differentiating among the various measures of time (Campbell et al., 2015). Knowing the human attention level helps improve human working and study efficiency (Berka et al., 2007; Sun et al., 2014). A study about attention in the psychology field was introduced by Wilhelm Wundt (Titchener., 1921). In 1868, Franciscus Donders investigated reaction time toward attention by using chronometry. Which the meaning of chronometry is the study about temporal sequencing of information in the brain (Donders. 1969). In the 1990s, positron emission tomography (PET) is started to be used for attention studies (Petersen et al., 1988; Posner and Petersen. 1990; Burton et al., 1999). In 1993, Osman et al (Osman et al., 1993) mentioned that attention can also affect EEG signals associated with later central processing stages, such as those involved in the selection and initiation of responses. Research about attention also has been investigated by using Electrocardiogram (ECG) (Borger et al., 1999; Smallwood et al., 2004; Griffiths et al., 2017). Investigation of attention toward hemodynamic activity has been measured by using Near-Infrared Spectroscopy (NIRS) (Matsuda and Hiraki. 2006; Toichi et al., 2004; Derosière et al., 2013). Nowadays researchers are not only trying to investigate the effect of attention toward physiological activity, but also trying to establish some methods to detect attention level automatically.

Generally, there are two main tasks in machine learning. They are unsupervised and supervised machine learning (Russel et al., 2010). The main differences between the two types are that supervised learning is done by data labeling and the goal is to learn a function that given a sample of data and desired output. Supervised machine learning is a method in machine learning by using knowing labeling methods to label the data and has the expecting result (input-output pairs) (Stuart et al., 2010). Unsupervised machine learning, on the other hand, is not based on data labeling and its goal is to infer the natural structure present within a set of data points. Measuring human mental states based on physiological activity has also been investigated by integrating EEG and ECG features (Stikic et al., 2014). The unsupervised method has been applied for cognitive state recognition in that experiment. However, the unsupervised learning requires large amounts of data to get an appropriate pattern and also there is no certain validation method to validate the data. In my study, data labeling relied on physiological activities.

Inattention level detection, there are 4 methods commonly used. They are observation, objective performance, self-assessment, and physiological activity. The classification of attention based on self-reporting and observation tends to be delayed, sporadic, and intrusive. Performance-based information can be misleading since multiple degrees of tasks could be grouped with the same level of performance. Conversely, physiological measures can be arranged to have little or no interference with task execution and can supply information continuously without significant delay (Yurko et al., 2010; Sun et al., 2014; Aghajani et al., 2017).

This study aims to label attention level using pupillometry, which can be further used in a supervised machine learning system of attentional evaluation. In this thesis I focused on how to establish the algorithm for new labeling by using pupillometry, after that, I applied the label and established the model algorithm based on supervised machine learning on EEG-ECG-NIRS for attention level detection.

As the task design, I used common attention task test which is digited span forward and backward (Jensen et al., 1975; Cullum., 1998; Berka et al 2007, Zennifa et al., 2018; Zennifa et al., 2019), and additionally, I also applied the arithmetic test (Zennifa et al., 2018; Zennifa et al., 2019). Most of the questions in this experiment were relatively simple and did not require any prerequisite knowledge or specific skills. However, a good level of attention and alertness was required to avoid making easy mistakes. There were several problems need to solve before taking the experiment. All participants had a normal visual function, were not with a disability and could do the experiment without wearing glasses. I also asked participants to have breakfast and not drink any caffeine before taking the test. Some participants did not follow this rule, and we have to exclude their data.

I am currently implementing a parameter setting based on features of pupillometry and for data labeling, I used Weka 3.8 (Hall et al., 2009) data mining for machine learning. I also applied a CFS + KNN algorithm on an EEG-ECG-NIRS system and used a searching algorithm which is called “best first”.

In the next section, I reviewed basic knowledge of attention level detection and blink rates, pupillometry and also EEG-ECG-NIRS. Furthermore, I introduced the related literature about attention level detection.

1.1 Some basic notions

1.1.1 Attention level detection.

Attention is the behavioral and cognitive process of selectively concentrating on a discrete aspect of information, whether deemed subjective or objective while ignoring other perceivable information. Knowing human attention is useful for efficiency in both working and studying (Berka et al., 2007, Sun et al., 2014).

There are 178 journals and magazines about attention level detection in the current past 10 years based on *IEEE explore*. There are 16 articles about "attention level detection" based on *google scholars* within 10 years. There are 139 journal articles about "attention pupillometry" based on *pubmed.gov*. Attention level detection has been done (by D.Das et al., 2013) in two classifications high attention and low attention based on behavioral pattern analysis. They used a robot as an observer to captures the attention of the person. But this research purely based on participant behavior. Another researcher (Sun et al., 2014), by using facial expression try to detect the attention level which accuracy up to 77.81%. By using facial expression is also depends on country culture. (Hussain et al., 2014) investigated the activity of physiological signals and facial responses to cognitive load under an emotional stimulus and collected participant ratings from a self-assessment manikin to find the normative ratings in the collection. They investigated the correlation between physiological data and the level of stimulation. They also subsequently compared the accuracy of cognitive load detection with face video features, physiological features, and participant rating features with fusion features. They concluded that classification with fusion features (i.e., not only based on self-report) performed with more accuracy. In my study, I proposed to establish a new labeling method for attention level detection and using the labeling data to train data from EEG-ECG-NIRS.

1.1.2 Blink rates and Pupillometry

In this study, I used EOG (electrooculogram) to measure blink rates and eye tracker to record pupillometry. EOG records eye movements by measuring electrical potential differences between two electrodes. This takes advantage of the fact that the human eye is an electrical dipole consisting of a positively charged cornea and a negatively charged retina, first discovered by Schott in 1922 (Muller et al 2016). When I used EOG, blink specify by amplitude more than 150 μV (Zennifa et al 2018.,; Bulling et al., 2011; Abo-zahhad et al., 2015; He S., 2017). Blink rates are the number of blinks at specific times. Eyeblinks are actively involved in the release of attention (Nakano et al, 2013). (Marc et al, 2015) evaluated spontaneous eye blink rate (SEBR) and percentage of incomplete blinks in different hard-copy and visual display terminal (VDT) reading conditions, compared with baseline conditions. In that study, they concluded that high cognitive demands associated with a reading task led to a reduction in SEBR, irrespective of the type of reading platform. However, only electronic reading resulted in an increase in the percentage of incomplete blinks, which may account for the symptoms experienced by VDT users. Blinking has been correlated with cognitive activity (Paprocki et al., 2017). Their study mentioned that blink rate carry information about cognitive performance and can be employed in the assessment of cognitive abilities without taking a test. Blink rate for mental states is performed by (Ren et al., 2019) in their paper, they attempted to differentiate between high and low cognitive loads of an individual through the analyses of BR and BRV (blink rate variability). The result indicated that BRV achieves significantly higher AUC values than BR, which suggests its strong potentiality for MSR. In sum, the BRV may prove to be a promising method for the MSR, which should be considered in the future.

Pupillometry is the measurement of pupil size and reactivity. It is also used in psychology (Granholm et al., 2004). Pupillometry is concerned with changes in pupil size. The diameter of the pupil size has long been known as a marker of cognitive load and attentional performance (Karatekin et al., 2007; Tsukahara et al., 2016; Hartmann et al, 2014; Geva et al., 2013; Unsworth et al., 2017 a&b; Piquado et al., 2010). A study by (Rud L van Den et al., 2016) mentioned that pupil size could be used to track the focus of attention. (Smallwood et al., 2011) concluded in their research that pupil dilations not only provide an index of overall attentional effort but are time-locked to stimulus changes during attention (but not during mind-wandering). This finding suggests that pupil dilations afford a dynamic readout of conscious information processing. Their finding later has been duplicated buy (Kang et al., 2014), demonstrating stimulus-pupil coupling from reflects online cognitive processing beyond sensory gain. The usage of pupillometry for attention research also used by (Naber et al., 2013). In their research, they used pupil frequency tagging (PFT) method to see the connection between cortical centers with visual selective attention. They concluded that the amplitude of pupil responses closely follows the allocation of focal visual attention and the encoding of stimuli. (Van der Wel et al., 2018).

1.1.3 EEG, ECG, NIRS research toward attention

Numerous methods using electroencephalograph (EEG), electrocardiograph (ECG), and near-infrared spectroscopy (NIRS) for the recognition of attention level and cognitive tasks have been proposed (Iramina et al., 2010; Zennifa et al.,2015; Shin et al., 2018;)). A study by (Chang et al., 2012) examines the brain oscillatory activities and peripheral physiological measures were influenced by attention levels. In their study, the level of attention is based on task difficulty. Their research mentioned that heart rate, heart rate variability, response rate, eye blinks, and skin conductance could be considered as promising indices for discriminating attention levels.

A wearable integrated electroencephalograph (EEG) and electrocardiograph (ECG) has been adapted for measuring the change of neurophysiological and autonomic activity in attention level, for autism spectrum disorder children. Attention level, which is determined as engagement states are labeled by observation method from 2 observers. By extracting quantitative EEG (QEEG) features from an EEG signal, as well as heart rate and heart rate variability (HRV) from an ECG, they found evidence of differing activity in the engagement and disengagement states, in both the EEG and ECG (Billeci et al., 2016). Near-infrared spectroscopy (NIRS) has been applied to assess anterior frontal hemodynamic responses to attention during three cognitive tasks. In their study, instead of doing engagement detection, they presented evidence of age-related anterior frontal hemodynamic changes with cognitive demands. (Bierre et al., 2017). Another attention level detection has also done by using SSVEP (Punsawad et al., 2017), the attention is categorized based on the EEG signal when the alpha ratio is decreased, and the beta ratio is increased than baseline. They got the accuracy of their data based on an algorithm is 81 %. (Liu et al., 2013) developed attention recognition by using single channels EEG. The labeling process in their research used participant self-assessment. In their research, they found the accuracy signal is 76.82% by using the SVM algorithm.

1.2 Thesis overview

This thesis consists of 4 chapters. Chapter 1 talking the general introduction of my study. I mentioned several studies that have done a similar experiment or some studies which become the basis of this study.

Chapter 2, I explained about the effect of blink rates and pupillometry toward attention level. In this chapter, we compared several methods for attention level detection such as; self-assessment, objective performance, observation, and our quantitative formula. I also explained the process to develop an algorithm for labeling the data to our model (EEG-ECG-NIRS) this chapter is based on the study by (Zennifa et al., 2019). The experiment in this chapter has been done for investigating the blink rates and pupillometry and evaluate it based on participant self-assessment.

Chapter 3, I talked about the application of the quantitative formula in supervised machine learning to our model (EEG-ECG-NIRS). In this chapter, participants did BDS, FDS, arithmetic tasks. For each task, there were three different cognitive task levels: Level one consisted of 30 trials with four digits in each trial; Level two consisted of 30 trials with five digits in each trial, and level three consisted of 30 trials with six digits in each trial. I recorded EEG, ECG, NIRS, eye tracking and EOG simultaneously. These experiments aim to collect the data and applied the quantitative formula in data labeling for further application in supervised machine learning.

Chapter 4, The last chapter in this study, we talked about the general discussion of this thesis. This chapter aims to mention all founding that we have and the limitation of my study.

1.3 Purpose of this study

I am currently implementing an EEG-ECG-NIRS (hybrid technology system) that can be used to evaluate attention levels during cognitive tasks. Several studies on the hybrid system have mentioned their promising characteristics. (Ahn et al., 2017) have suggested computational integration methods to achieve a hybrid EEG-NIRS system for mental fatigue states. However, the multimodal EEG-NIRS system in their study is a high-density type, which requires many channels data. (Hong et al., 2018) focused on the utility of the integration between EEG and NIRS for locked-in syndrome patients. They mentioned that the proper selection of features will improve the accuracy of classification. In my study, I investigated the features that can be used in attention level detection; the difference lies in the approach of the study. (Ahn et al., 2016) combined EEG, ECG, and NIRS by using 68 electrodes for EEG, ECG, and EOG and 8 channels in the NIRS in simulated driving. In my study, I use a two-electrode EEG, an ECG, and two channels in the NIRS. All the mentioned sensors are wireless. Previous work (Iramina et al., 2010; Zennifa et al., 2015) used this system for monitoring the cognitive state in children with developmental disorders during a 7 year training period. This time I would like to do attention level detection of the low-density hybrid system.

I investigated nine types of linear and nonlinear features from EEG, ECG, and NIRS to find the most common features that can be used in attention level detection. The investigation of linear and nonlinear features has been previously studied for mental state recognition but in stand-alone systems, such as only for EEG or ECG (Zakeri et al., 2017; Li et al., 2018; Huang et al., 2018). In my study, I tried to adapt these features to the hybrid system. This step was improved by combining the feature selector and classifier. I used the correlation-based feature selection (CFS) introduced by (Hall., 1999) as the feature selector and k-nearest neighbor (kNN) as the classifier, following several comparisons with other classifiers. Although a CFS and kNN combination (CFS + kNN) algorithm with two types searching method (i.e., best first search and greedy stepwise search) has been used by (Hu et al., 2018). My study applied a CFS + kNN algorithm in a low-density hybrid system and used one searching algorithm. In conclusion, the aim of this study is to propose a new labeling method for attention level recognition using pupillometry and applied it in EEG – ECG – NIRS system.

Chapter 2. New Labelling method for attention level detection

2.1 Abstract

Attention is described as a state in which an individual involved in an activity can ignore other influences. The attention level is important to obtain good performance, especially under study conditions. Numerous methods for attention level detection such as observation, self-assessment, objective performance and physiology signal has been applied. In this chapter, I tried to develop a labelling method based on physiological data (blink rates and pupillometry).

In this chapter, I compared the self-assessment method with other attention level detection methods (observation and objective performance). The aim of this comparison is to know the differences evaluation between self –assessments and other methods. From this comparison, I got the difference of self-assessment toward other method is lower than 21%. After that, I investigated the effect of attention level based on self-assessment to blink rates, and pupillometry. I found that pupillometry in low attention is smaller than high attention especially in the last 4 second encoding time ($P<0.05$). On the other hand, I did not get a significant difference in blink rates. After that, I calculated the distribution fit of pupillometry reaction in the attention level of all participants and plot the critical point of pupillometry data in 10 seconds and 4 seconds. After doing several experimental procedures, I chose parameter setting by comparing with self-assessment with a percentage of error of less than 15% and a different error 35 % as future labeling method. Parameter setting which has been selected is when z-score within a specific range ($-0.965 \leq$ pupil ≤ 1.014) as high attention, other that range, will be classified as low attention.

2.2. Materials and Methods

2.2.1 Participants

There were 18 participants in my experiment. All participants were Kyushu University students, with ages ranging from 21 to 29 (23.5 ± 2.18). All participants had a normal visual function and were free of disability; 15 were right-handed, 1 participant was ambidextrous, and 2 participant was left-handed. Participants were instructed not to consume any caffeine 2 h before the experiment because it could affect the HRV (Martínez-Sellés et al., 2013; Oliveira et al., 2017). The study was conducted by following the ethical principles of Kyushu University and the Declaration of Helsinki. Written informed consent was obtained from each participant before the experiment as showed on **Appendix 1**.

2.2.2 Experiment condition

The experiment took place in a dimly lit room. I also recorded the behavior activities using a webcam camera (Logicool C270, Logitech, Switzerland), which was located around 57 cm in front of the participant's face.

Three types of attention task were used: backward digit span (BDS) (Jensen et al., 1975; Cullum., 1998; Berka et al 2007, Zennifa et al., 2018; Zennifa et al., 2019; Rosenthal et al., 2006), forward digit span (FDS) (Jensen et al., 1975; Cullum., 1998; Berka et al 2007, Zennifa et al., 2018; Zennifa et al., 2019; Rosenthal et al., 2006) and arithmetic (Zennifa et al., 2018). These tasks consist of three-level. Level one consisted of a series of 20 sets of four digits, level two: 20 sets of five digits and level three: 20 sets of six digits. Most of the questions in this experiment were relatively simple and did not require any prerequisite knowledge or specific skills. However, a good level of attention and alertness was required to avoid making easy mistakes because the response time was limited to 15 s. Each trial started with the presentation of a central, white fixation dot on a dark background until the participant's eyes could be accepted by the eye tracker. Next, cognitive questions (i.e., encoding session) would appear for 10 s and the participant was instructed to respond within 15 s. Digits will appear every 2.5 seconds in 4 digit level, 2 seconds in 5 digit level and 1.67 seconds in 6 digit level. After that, participants should report their attention level in two conditions, high or low. All cognitive tasks were counterbalanced. The measurement was recorded after the practice session finished. The task can be seen in **Figure1.**

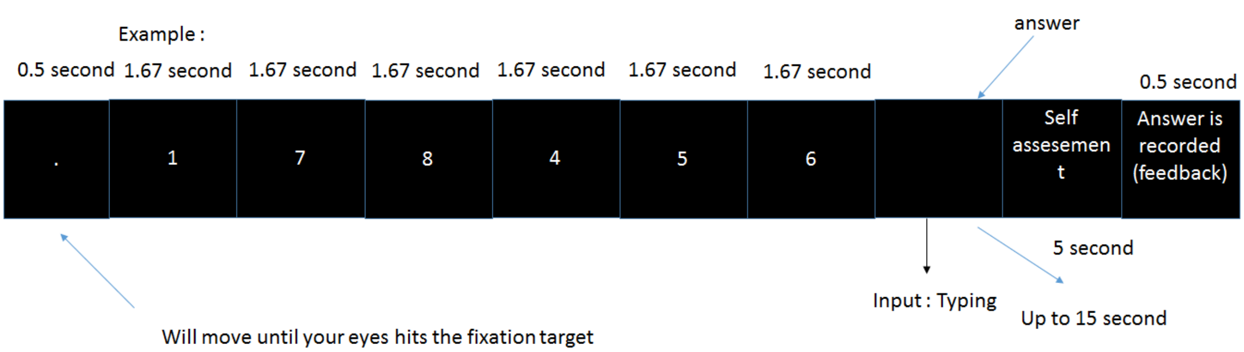


Figure 1. Task design example

2.2.3. Software and Apparatus

In this chapter, the 17-inch CRT monitor (1024 × 768) has been used for presenting the stimuli. Testing took place in a dimly lit room. Stimuli presentation was done by using OpenSesame (Mathôt et al., 2012), using the legacy back end for the display control and the PyGaze toolbox (Dalmaijer., 2014) for integrating to the eye tracker.

2.2.3.1 Eye Tracking

Before the start of each task, participants were positioned in front of an eye tracker (The EyeTribe tracker version 1, Copenhagen, Denmark). The distance of the participants' eyes from The EyeTribe was estimated to be ~57 cm. The participants were asked to fix their heads on a chin rest. In this study, we calibrated and validated the eye-tracking system to each participant using a nine-point dot matrix. After validation, the eye tracker that had been embedded with the OpenSesame software labeled each calibration point with the error in the degree of the visual angle between the calibrated and validated measures. If the calibration points do not exceed 1° (degree) and the greatest single point error does not exceed 1°, the process would continue. Before each trial, a one-point eye tracker recalibration was performed.

2.2.3.2 Electrooculogram

In this study, EOG (Polymate Mini AP 108, Miyuki Giken Co., Ltd., Kasugai-city, Japan) signals were sent by Bluetooth to a computer. The frequency of sampling was 500 Hz. We put two electrodes for a vertical EOG. This location was chosen to detect blink(Waters et al.,2005 ; Huang et al, .2018). **Figure 2** shows the electrode placements.

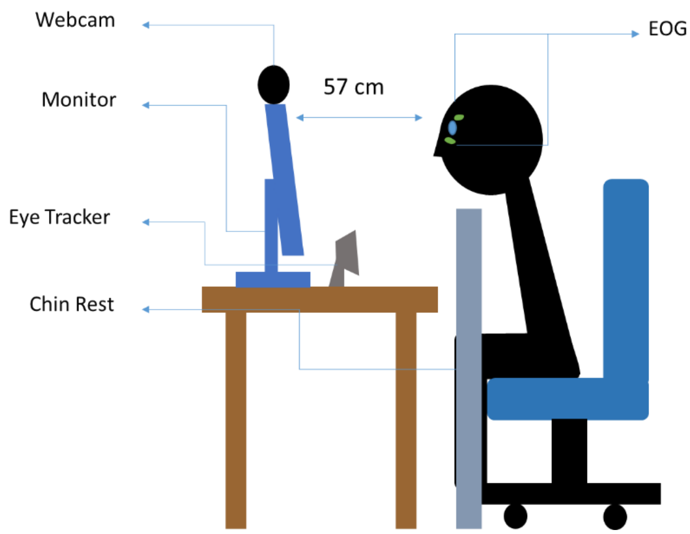


Figure 2. Position of the participant during the experiment

2.3 Data Analysis

2.3.1 Comparison system from all attention level detection method

In this study, I compared the accuracy recognition from self-assessment to another detection method (observation and performance). This analysis aims to know the similarity accuracy recognition. The example of calculation can be seen in **Table 1**.

Table 1. Accuracy comparison self-assessment vs other methods.

Other parameters	**Self-assessment**	**Status**
High	High	True
High	High	True
Low	High	False
Low	Low	True

Based on data from **Table 1**, I calculated difference rate error and error rate detection based on formula (1) and formula (2).

$$\text{difference rate detection } (\%) = \frac{difference\ error}{total\ trials} \quad (1)$$

$$\text{error rate detection } (\%) = \frac{error\ detection}{total\ trials} \quad (2)$$

Difference error is difference status between self-assessment and another method in each trial. Error detection is the different status between self-assessment and another method in all trials. Total trials means the number of all trials that has been done by each participant.

2.3.2 Blink rates and pupillometry analysis

After getting results from participant self-assessment and another recognition method, I started to analyze the blink rates and pupillometry. I would like to check the effect of attention based on self-assessment toward blink rates and pupillomery. Below is the explanation how do I analyze blink rates and pupillometry.

2.3.2.1 Blink rates

I used EOG to detect the blink rates of our participants every 10 seconds (encoding time). Blinking has been correlated with cognitive activity. In this study, eye blinks were detected with vertical EOG. To analyze the EOG signal, I used MATLAB 2017b. We performed baseline drift removal. The EOG signal is characterized by a frequency range of 0.1 to 20 Hz, and the amplitude lies between 25 and 3500 μV. We applied a bandpass filter from 0.1 to 20 Hz. I selected the detected peak at more than 200 μV as the criterion (Bulling et al., 2011) for eye blinking. The process of blink detection is explained in **Figure 3**, as follow:

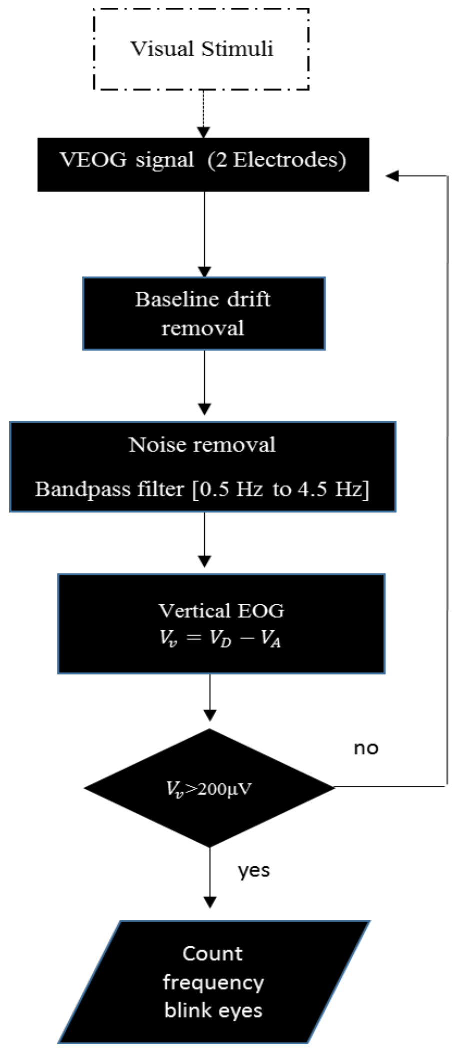


Figure 3. Blink detection

2.3.2.2 Pupillometry analysis

Pupillometry is concerned with changes in pupil size. The diameter of the pupil size has long been known as a marker of cognitive load and attentional performance. A study by (Van Den et al., 2016) mentioned that pupil size could be used to track the focus of attention. When using eye-tracking for recording pupil size, there was missing data. To solve the problem, I did cubic spline interpolation (Koening et al., 2017; Kang et al., 2014; Dalmeijer et al., 2014; Van der Brink et al 2014) in our data to reconstruct the signal, and connecting the missing data. **Figure 4** is shown signal differences before interpolation and after interpolation.

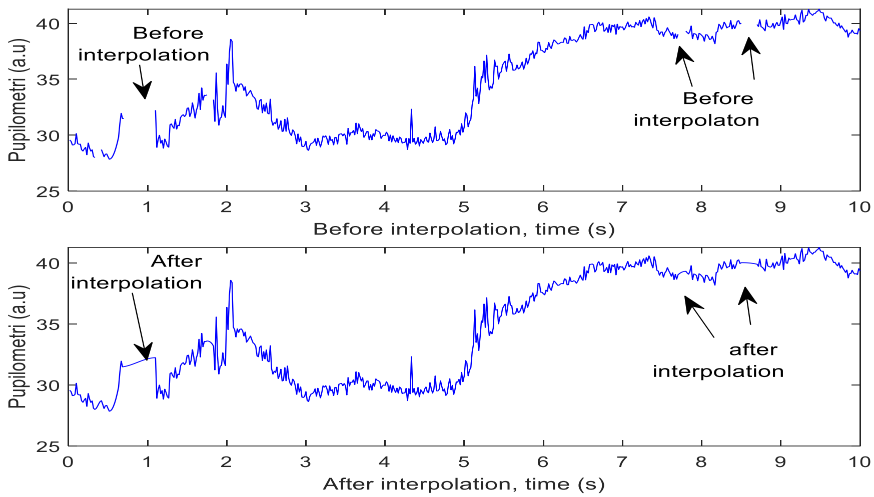


Figure 4. Signal reconstruction

In this study, I analyzed pupillometry using a handmade program written in Matlab 2017b. The process is started by detecting missing data or signal with less than 20 pixels will be replaced with NaN then applied cubic interpolation to reconstruct the data.

The analysis process can be seen in **Figure 5**.

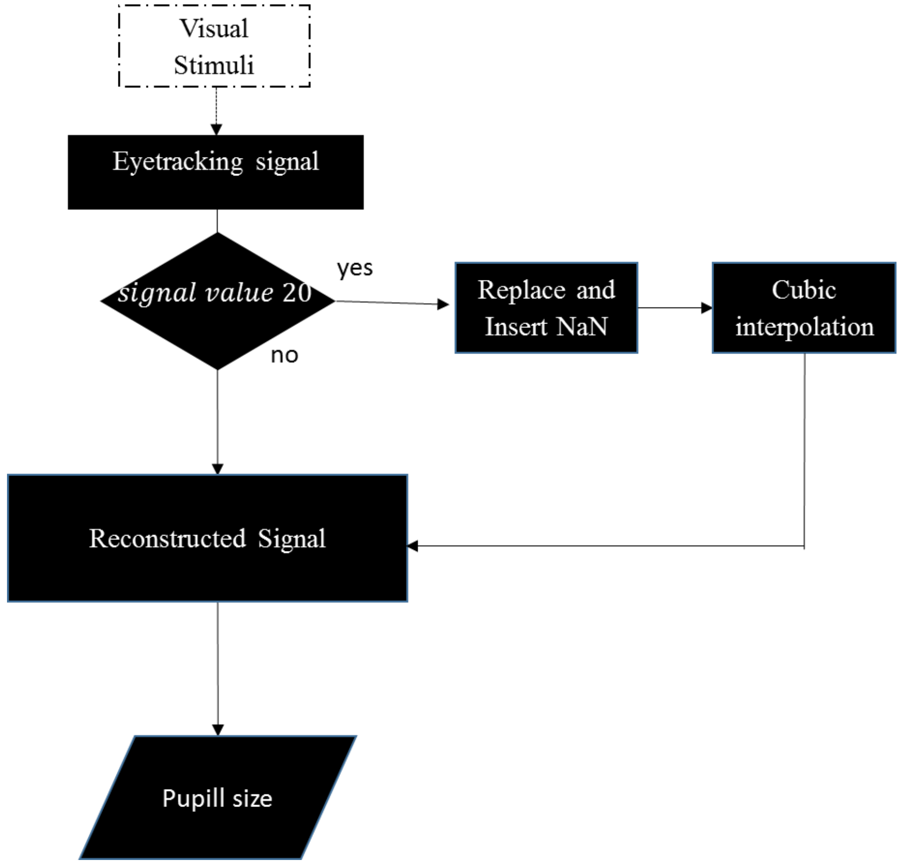


Figure 5. Pupillometry analysis

After getting the value of pupil size, considering difference of each individual data, I converted the value of raw pupillometry to Z-score, as showed in **Equation (3)**:

$$Z_{\text{pupil}}=\frac{x_{sample}-\mu_{population}}{Sd_{population}} \quad (3)$$

Where x_{sample} is participant pupillometry in each trial.

$\mu_{population}$ is average participant pupillometry in all trials.

$Sd_{population}$ *is standard deviation of pupillometry in all trials*

2.3.2.3 Data balancing

Because my data based on states (High attention and Low attention) are imbalances, I need to anticipate this event by re-sampling my data (Chicco et al, 2017). In my study, I applied oversample technique as solution for my imbalance data. Oversampling means to increase the number of minority class members in dataset. By using over-sampling there is no information from the original training set is lost since all members from the minority and majority classes are kept. (Rahman et al., 2013; Chawla et al., 2018). Balancing is applied when plotted histogram all participants data into one dataset.

2.4 Results

There are 18 participants joined to this experiment, but four of them has to be excluded due to technical problem. In this thesis, we used 14 participant's data to establish the algorithm. Considering there was a difference in each participant's physiological activity, we calculated the value of participants z-score based on **Equation (3)** to normalized the data and manage the data into one datasheet. There are data point 2520 in my datasheet. Data management can be seen in **Figure 6.**

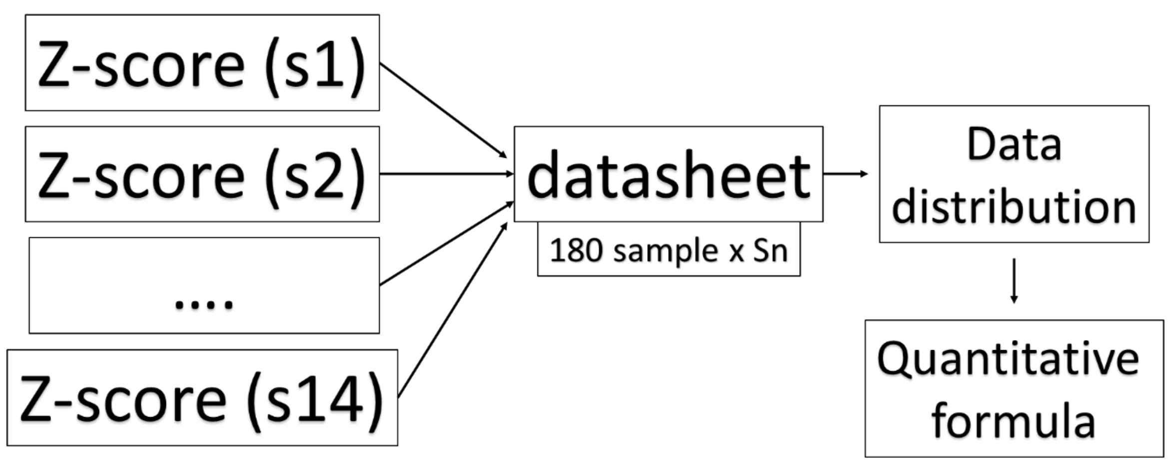


Figure 6. Data management

2.4.1 Self-assessment reliability for the basis on quantitative formula

2.4.1.1 Self-assessment vs Objective behavior

This part, I tried to investigate the difference between self-assessment and objective behavior toward attention level detection. Based on objective behavior, if the participant's response in a trial is incorrect, the current level of attention is marked as "low attention"; In contrast, if the response is correct, the current attention level is marked as "high attention. Based on formula (1) and (2) I compared the objective behavior and self-assessment. From this calculation, I found that the average error rate is 15±19.0 % and the average error is 20±17.9%. The detail can be seen in **Table 2**.

Table 2. Self-assessment vs Objective behavior

	Error rate	**difference error**
S1	7%	16%
S2	9%	13%
S3	33%	37%
S4	14%	18%
S5	12%	14%
S6	8%	17%
S7	4%	4%
S8	1%	7%
s9	4%	8%
S10	3%	2%
S11	63%	64%
S12	52%	54%
S13	1%	12%
S14	3%	13%
average	15%	20%
SD	0.190429161	0.179302788

2.4.1.2 Self-assessment vs Observation

Similar to the previous part, in this part, we also investigated the difference between self-assessment and observation methods regarding attention level detection. Observation has been done by the author of this thesis and in this thesis, high attention is defined when the participant's eyes look at the monitor. When participants look away from the monitor, we categorized it as low attention. From our calculation we got the average error rate is 16±14.2%, difference error is 16±14.1%. The detail can be seen in **Table 3.**

Table 3. Self-assessment vs Observation

	Error rate	Difference error
S1	18%	18%
S2	18%	18%
S3	37%	37%
S4	19%	19%
S5	14%	13%
S6	13%	14%
S7	6%	7%
S8	6%	6%
S9	8%	8%
S10	4%	4%
S11	4%	4%
S12	58%	58%
S13	12%	11%
S14	11%	11%
Average	16%	16%
SD	0.142097983	0.141846425

2.4.1.3 Blink rates histogram based on self-assessment

I calculated blink rates of 14 participants during 180 trials. When I performed a t-test to compare the blink rates during that high attention and low attention, with alpha value 0.05, By doing a t-test, I found there is no significant difference (P=0.605678)**.** Blink rates data can be seen in **Table 4**.

Table 4. Blink rates during trials

	High attention	Low attention
S1	1	2
S2	1	0
S3	3	2
S4	1	1
S5	1	1
S6	1	2
S7	3	4
S8	3	4
S9	1	1
S10	1	1
S11	3	3
S12	3	3
S13	1	1
S14	5	6
Average	1.997974	2.066987
SD	1.339705	1.517106

2.4.1.4 Pupillometry based on self-assessment

I calculated pupillometry based on temporal analysis and I divided the data based on self-assessment classification. Based on my investigation, I found pupillometry during high attention (**Figure 7**) and low attention (**Figure 8**) has a different characteristic.

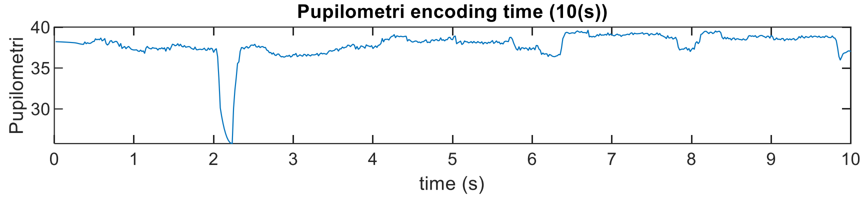


Figure 7. High attention in each trial

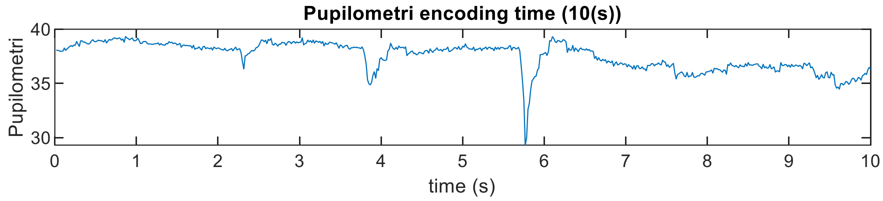


Figure 8. Low attention in each trial

After calculating the data from each participant in each trial, I found that average pupil size in pupillometry has a tendency to be decreasing in low attention and tends to be stable in high attention in the temporal analysis. Following that, I also found that pupillometry in high attention has a bigger size rather than in low attention.

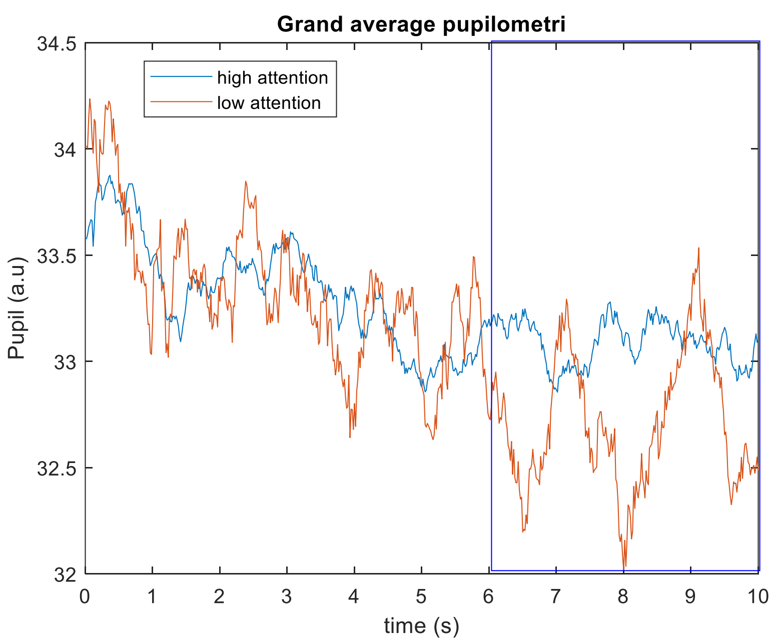


Figure 9. Temporal analysis pupillometry n= 14

I did the further investigation by calculating the differences of pupillometry activity at the beginning of 6 seconds and the last 4 seconds of the encoding task from **Figure 9 on this two attention levels**. I found there is no significant difference (P>0.05) by using Wilcoxon rank-sum on the continues signal in beginning of 6 seconds. But I found there is significantly different on the continues signal by using Wilcoxon rank-sum test (P<0.05) last 4 seconds. Table 5 shows the average pupillometry in each participants based on attention levels.

Table 5. Average pupillometry in each subject

	Beginning 6 second		Last 4 Second	
	High attention	Low attention	High attention	Low attention
S1	31.83368	33.42625	31.04758	31.18264
S2	34.77668	32.40753	33.5032	30.27424
S3	23.33582	23.95336	24.35332	23.99374
S4	26.44845	26.01096	26.25718	25.31754
S5	33.18858	33.35039	33.25034	33.85547
S6	37.72262	38.13709	37.85865	37.77368
S7	34.00407	34.05662	33.61359	33.76792
S8	37.52127	36.83961	37.15663	35.11022
S9	36.4444	35.90752	36.19968	35.18421
S10	36.56941	37.23889	36.8433	37.48195
S11	32.62384	32.99973	32.09949	32.2347
S12	32.2439	30.8706	32.52735	30.82266
S13	31.88902	34.01617	30.58318	33.03103
S14	38.0648	37.46423	37.96614	37.89966
Average	33.33333	33.33421	33.08997	32.70926
SD	4.25417	4.150505	4.132913	4.074638

I plotted data of all participants in all trials into one histogram. Plotting the data into one dataset and a histogram has been decided due to the small numbers of my data. So instead plotting the histogram of 14 data point (because there are 14 participants), I plotted histogram of 14 participants in all trials, and it cause my data points become 2520. Those data can be seen on **Figure 10.** I plotted pupillometry histogram data into 3 areas. Two areas are considered a critical area and one area is considered as non-critical area. The critical area is defined as anything less than the standard deviation, the non-critical area is defined as anything that greater than the standard deviation. From this histogram, the most frequent value from all participants during high attention is 35.75 and the most frequent value of low attention is 32.91.

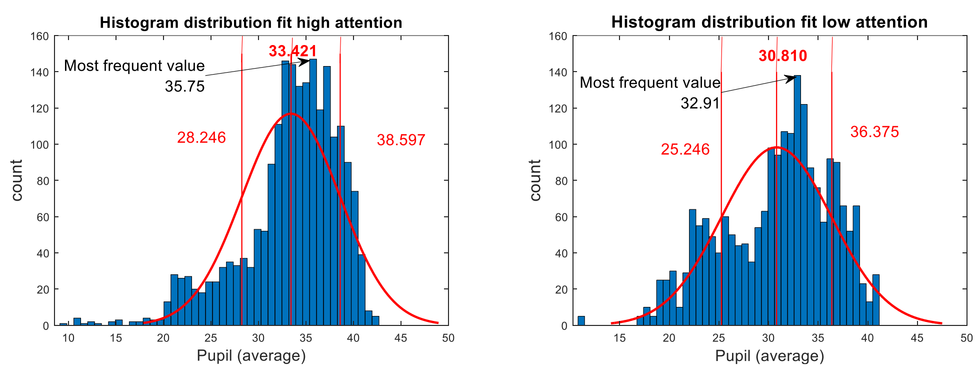


Figure 10. States last 4 second

Considering different activities from each participant, we converted raw pupillometry data into z- score value based on **equation 4 a**nd processed like **Figure 6** in each participant and convert them into one data sheet and plot histogram. Based on **Figure 11**, the most frequent value in high attention is 0.475 and low attention most frequent value is 0.107.

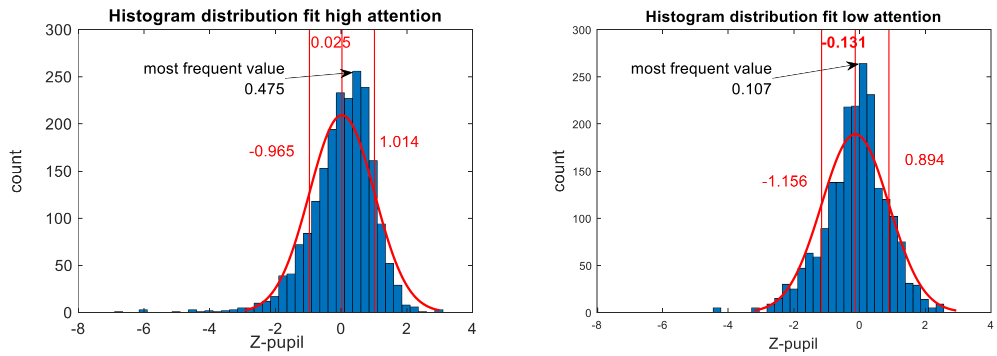
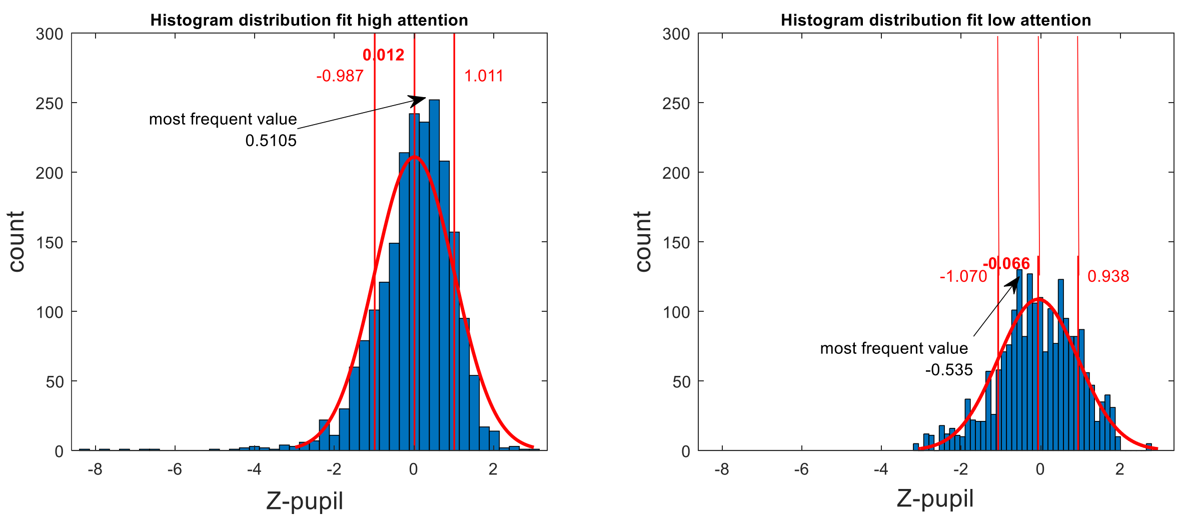


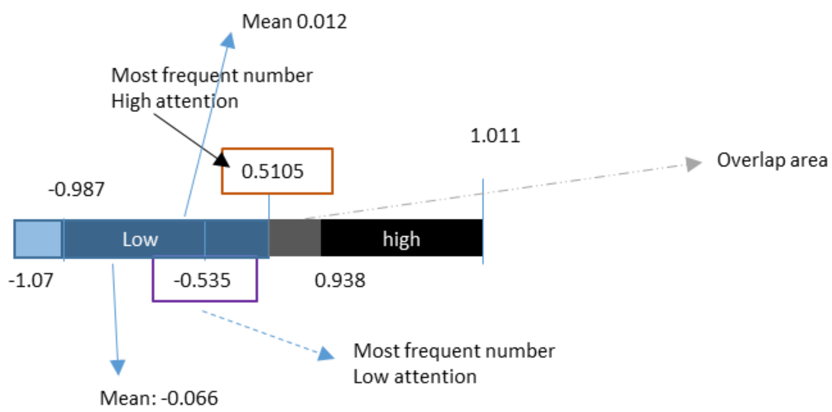
Figure 11. Z-score last 4 second

2.4.2 Parameter settings for attention level

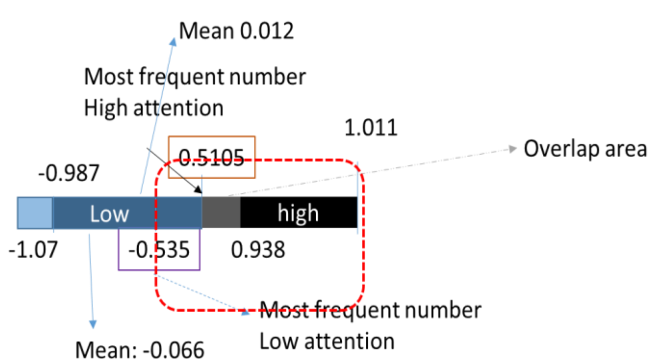
2.4.2.1 Extracting Pupillometry in 10 s to parameter settings

In this session, I tried to extracted data from histogram distribution during high attention and low attention to several thresholds for labeling. Average of ten-second data is used and converted to z-score, I divided data into 3 criteria (2 critical areas and 1 noncritical area). For further labeling is extracted from data in the non-critical area. The process to extract parameter setting for labeling is as follow:



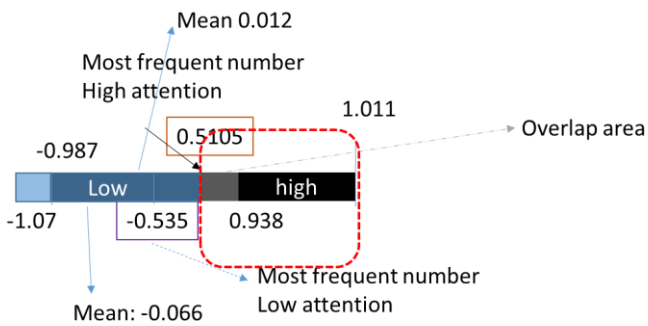


The first parameter setting in this method has been taken on the most frequent value of pupil during low attention (-0.535) and the maximum value of pupil high during high attention. In this case, if z- score of pupil equal or more than 0.025 and lower or equal to 2.972 data will be labeled as low attention.



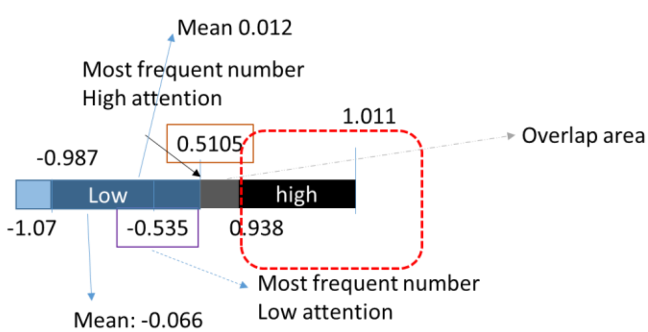
Parameter setting 1
If -0.535 < pupil So ("high attention") Else ("low attention")

The second parameter setting is extracted from the most frequent value during high attention (0.5105). If z- score of pupil size is bigger than or equal to 0.5105 we labeled the data as high attention.



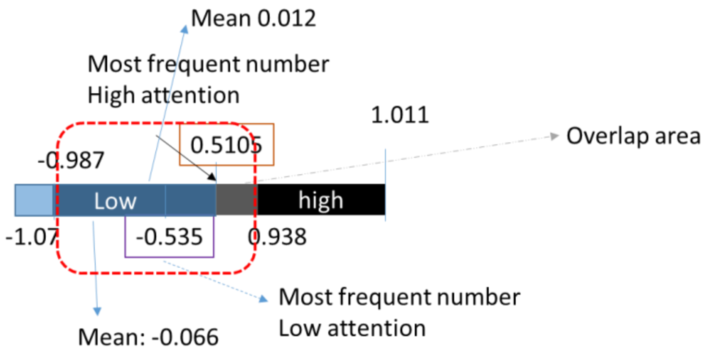
Parameter setting 2
If 0.5105 ≤ pupil So (“high attention”) Else (“low attention”)

The third parameter setting is extracted from the mean value of pupillometry during high attention (0.938). High attention will be labeled to data which has a value bigger than 0.938



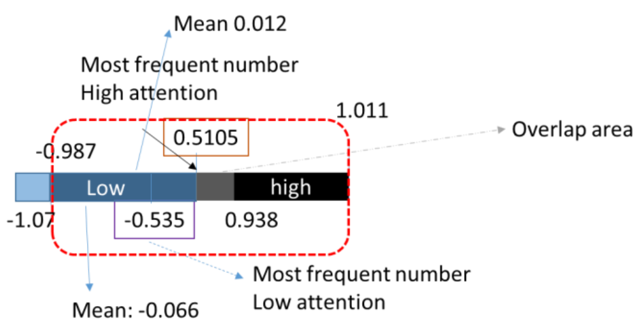
Parameter setting 3
If 0.938 < pupil So (“high attention”) Else (“low attention”)

The fourth parameter setting is extracted from the minimum value of pupillometry during low attention (-1.07) and the maximum value of pupillometry during low attention (0.938).



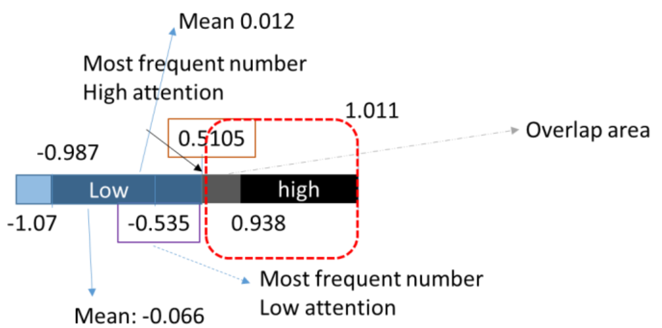
Parameter setting 4
If $-1.07 \leq$ pupil ≤ 0.938 So ("low attention") Else ("high attention")

The fifth parameter setting is based on a minimum value of pupillometry during high attention (-0.987) and minimum value during high attention (1.011). If z fulfilled the criteria, the data will be labeled as high attention.



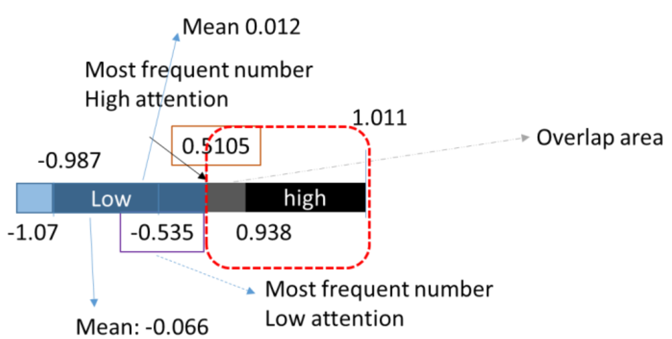
Parameter setting 5
If $-0.987 \leq$ pupil ≤ 1.011 So ("high attention") Else ("low attention")

The sixth parameter setting is based on the most frequent value of pupillometry during high attention (0.5105) and the maximum value of pupillometry (1.011). If the Z score of pupil size is fulfilled that criteria, data is labeled as high attention.



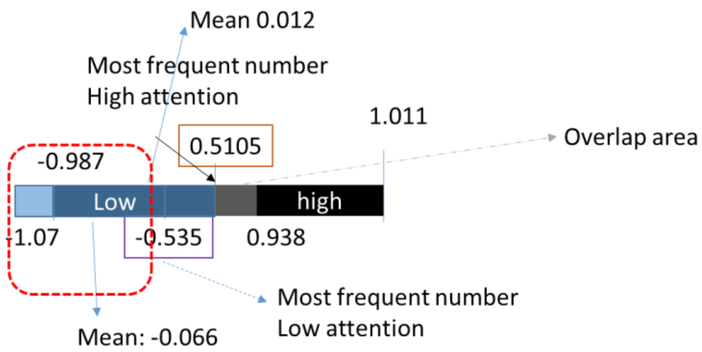
Parameter setting 6
If 0.5105 ≤ pupil ≤ 1.011 So ("high attention") Else ("low attention")

The seventh parameter setting is based on the minimum value of pupillometry during low attention (0.5105). If the Z score of pupil size is fulfilled the criteria, we labeled the data as low attention.



Parameter setting 7
If pupil < 0.5105 So ("low attention") Else ("low attention")

The eight parameter setting is based on the mean value of pupillometry during high attention (0.012). If the Z score is fulfilled that criteria, we labeled the data as low attention.



Parameter setting 8

If

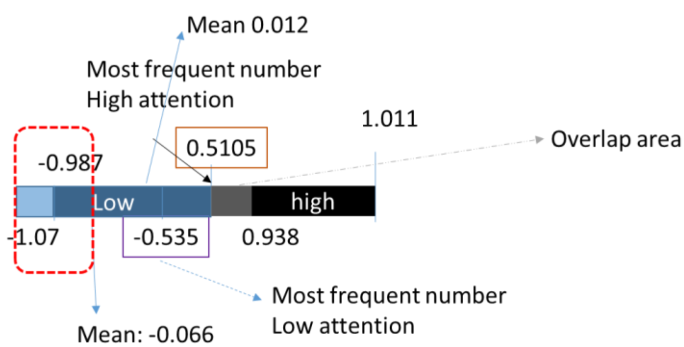
pupil < 0.012

So (“low attention”)

Else

(“high attention”)

The ninth algorithm is based on a minimum value of pupillometry during low attention (-0.066). If the Z score of pupil size is lower than -0.066, we labeled the data as low attention.



Parameter setting 9

If

pupil ≤ -0.066

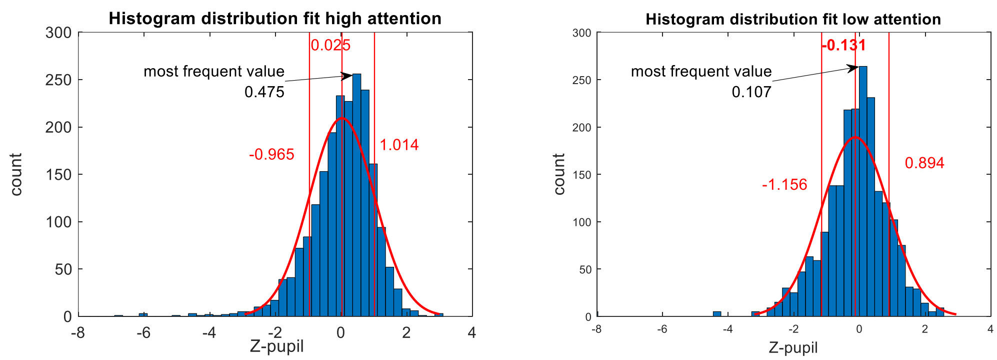
So (“low attention”)

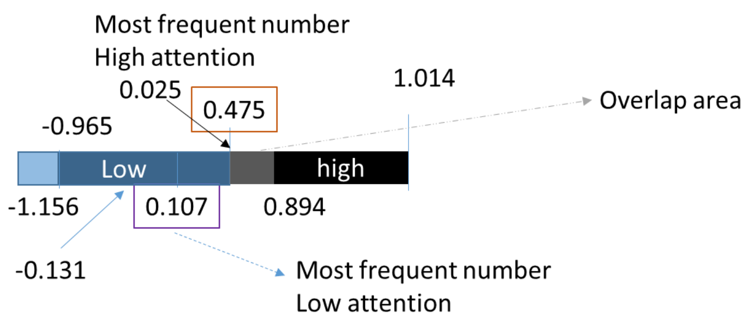
Else

(“high attention”)

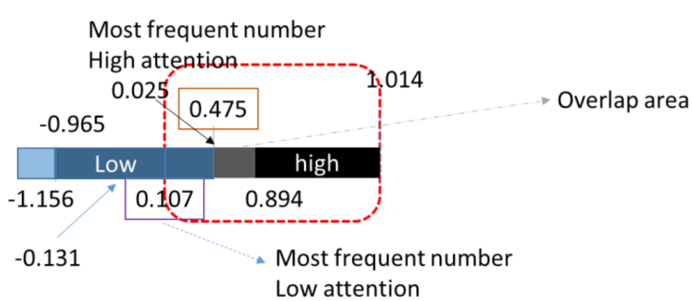
2.4.2.2 Extracting pupillometry data to parameter setting from last 4 second data

In this session, I tried to extracted data from histogram distribution during high attention and low attention to several labels. Average of 4-second data is used and converted to z-score, I divided data into 3 criteria (2 critical areas and 1 noncritical area). For further labels is extracted from data in the non-critical area I extracted the data into 9 experiments and converted the data into 9 parameter settings. These extraction based on the non-critical area from our z-score histogram. The process to extract the labels as follow:



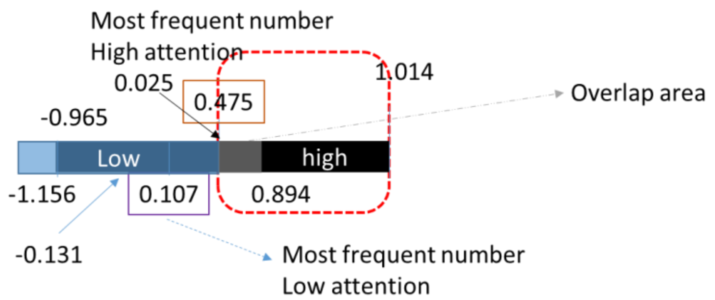


In the first experiment, the mean value of pupillometry in low attention based on self-assessment has been chosen as a threshold. If data is fulfilled the criteria of label 1 (z-score of pupil is bigger than 0.107), I labeled it as high attention.



Parameter setting 1
If 0.107 < pupil So (“high attention”) Else (“low attention”)

In the second parameter setting, the maximum value of pupillometry in high attention based on self-assessment has been chosen as a threshold. If z-score of pupillometry bigger than or equals to 0.475, I labeled it as high attention.



Parameter setting 2

If

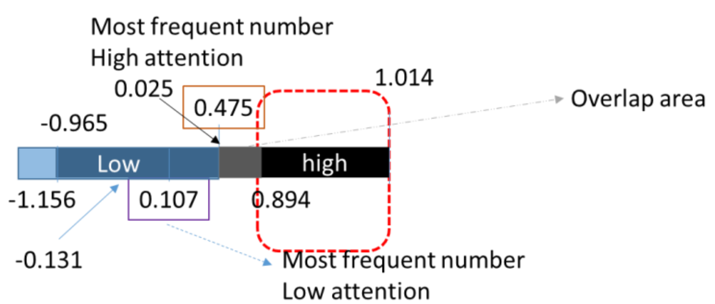
0.475 ≤ pupil

So (“high attention”)

Else

(“low attention”)

In the third parameter setting, the maximum value of pupillometry in low attention based on self-assessment has been chosen as a threshold. If data is fulfilled the criteria of algorithm 3 (Where people bigger than 0.894), I labeled it as high attention.



Parameter setting 3

If

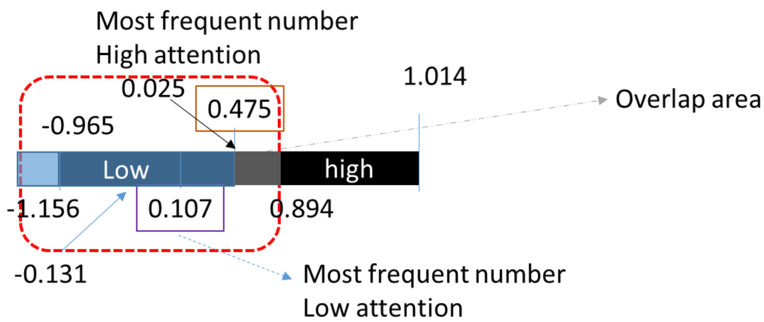
0.894 < pupil

So (“high attention”)

Else

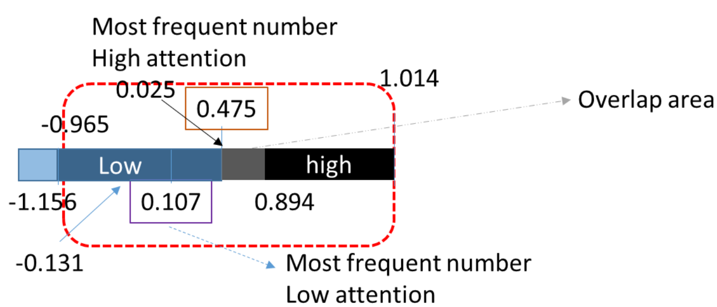
(“low attention”)

The fourth parameter setting t, the maximum value of pupillometry (0.894) and minimum value (-1.156) in low attention based on self-assessment has been chosen as a threshold. If data is fulfilled the criteria of algorithm 4, we labeled it as high attention.



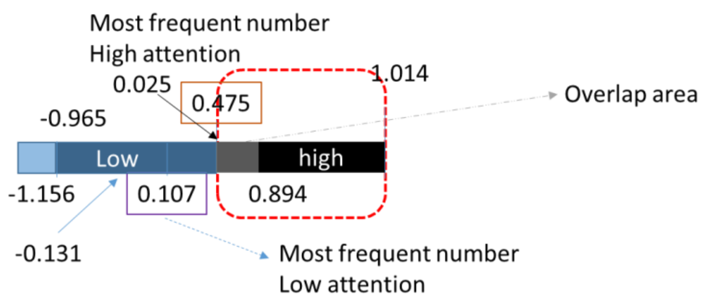
Parameter setting 4
If -1.156 ≤ pupil ≤ 0.894 So (“low attention”) Else (“high attention”)

The fifth parameter setting, the maximum value of pupillometry in high attention (1.014) and minimum value (-0.965) based on self-assessment has been chosen as a threshold. If data is fulfilled the criteria of this parameter setting, I labeled it as high attention.



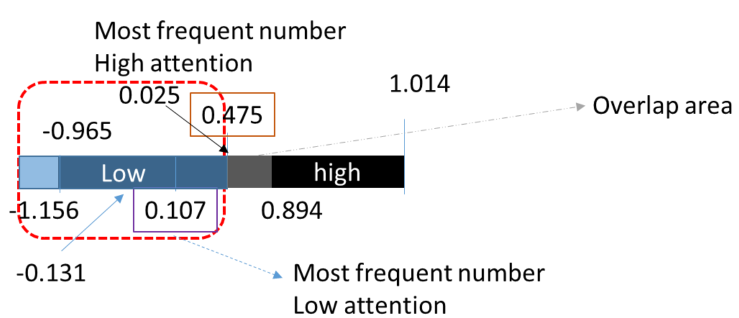
Parameter setting 5
If -0.965 ≤ pupil ≤ 1.014 So (“high attention”) Else (“low attention ”)

In the sixth parameter setting, the most frequent value of pupillometry (0.475) and maximum value (01.014) in high attention based on self-assessment has been chosen as a threshold. If data is fulfilled the criteria of algorithm 6, I labeled it as high attention.



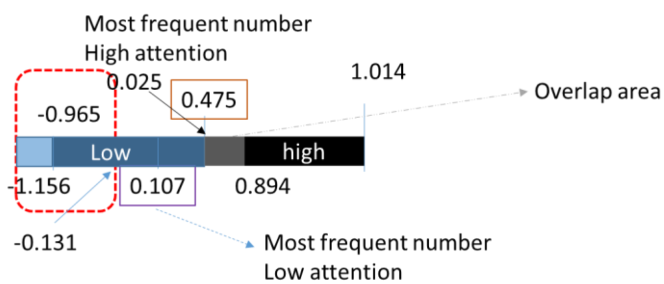
Parameter setting 6
If $0.475 \leq$ pupil ≤ 1.014 So ("high attention") Else ("low attention")

In the seventh parameter setting, the most frequent value of pupillometry in high attention based on self-assessment has been chosen as a threshold. If data is fulfilled the criteria of parameter setting 7 (z-score of pupillometry bigger than 0.475), I labeled it as low attention.



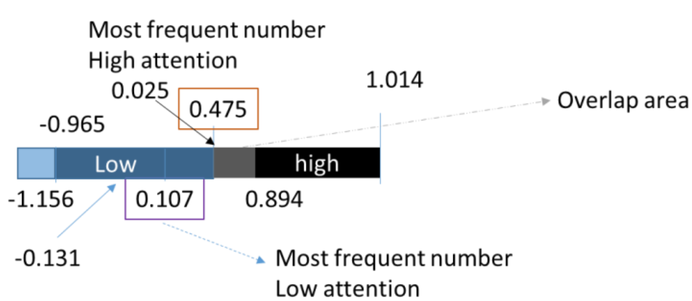
Parameter setting 7
If pupil < 0.475 So ("low attention") Else ("high attention")

The eight parameter setting, the mean value of pupillometry in high attention based on self-assessment has been chosen as a threshold. If data is fulfilled the criteria of parameter setting 8 (z-score of pupillometry is 0.025), I labeled it as low attention else than that is high attention.



Parameter setting 8
If pupil < 0.025 So ("low attention") Else ("high attention")

The ninth parameter setting, if pupillometry z-score lower than -0.131 I labeled the data as low attention, another condition is high attention.



Parameter setting 9
If pupil < -0.131 So ("low attention") Else ("high attention")

2.4.3. The error rate of quantitative for attention level

2.4.3.1 Pupillometry in 10 s

To validate my extracted algorithm, I compared the data labeled by quantitative formula and data based on self-assessment following formula from **formula (1) and (2)**. Here we compared the error rate which can be seen in **Table 6** and difference recognition in **Table 7**. The table which has grey shading shown the optimum value of error rate and difference recognition.

Table 6. Error rates in 180 trials pupillometry parameter setting

	Parameter setting **1**	Parameter setting **2**	Parameter setting **3**	Parameter setting **4**	Parameter setting **5**	Parameter setting **6**	Parameter setting **7**	Parameter setting **8**	Parameter setting **9**
s1	14%	52%	66%	51%	21%	69%	52%	31%	31%
s2	6%	43%	62%	44%	14%	58%	43%	24%	21%
s3	11%	34%	47%	36%	11%	48%	34%	17%	16%
s4	36%	47%	62%	54%	19%	64%	47%	34%	33%
s5	13%	56%	68%	56%	14%	71%	56%	34%	32%
s6	5%	61%	78%	71%	2%	68%	61%	36%	29%
s7	12%	68%	88%	84%	5%	74%	68%	41%	36%
s8	9%	48%	76%	61%	11%	56%	48%	22%	21%
s9	12%	56%	84%	72%	11%	62%	56%	28%	24%
s10	27%	62%	77%	62%	29%	78%	62%	43%	39%
s11	31%	9%	21%	8%	27%	26%	9%	5%	9%
s12	1%	77%	92%	89%	1%	78%	77%	40%	31%
s13	24%	54%	67%	49%	29%	76%	54%	41%	38%
s14	16%	57%	72%	56%	21%	72%	57%	34%	28%
Average	15%	52%	69%	57%	15%	64%	52%	31%	28%
SD	0.099599	0.155085	0.173582	0.194805	0.090068	0.135772	0.155085	0.102474	0.084192

Table 7. Difference recognition pupillometry *Parameter setting*

	Parameter setting **1**	Parameter setting **2**	Parameter setting **3**	Parameter setting **4**	Parameter setting **5**	Parameter setting **6**	Parameter setting **7**	Parameter setting **8**	Parameter setting **9**
s1	33%	62%	71%	64%	34%	74%	18%	47%	46%
s2	22%	52%	66%	65%	31%	64%	14%	34%	31%
s3	41%	55%	61%	53%	46%	57%	14%	47%	46%
s4	49%	56%	67%	59%	50%	68%	17%	50%	49%
s5	37%	68%	76%	65%	34%	76%	16%	49%	49%
s6	27%	67%	81%	76%	24%	73%	8%	49%	44%
s7	21%	71%	88%	84%	15%	77%	6%	47%	42%
s8	33%	61%	82%	68%	30%	63%	8%	44%	43%
s9	26%	63%	88%	77%	24%	67%	6%	38%	37%
s10	33%	66%	79%	65%	34%	80%	16%	48%	45%
s11	45%	37%	36%	43%	56%	42%	17%	36%	36%
s12	8%	78%	92%	89%	10%	79%	2%	46%	37%
s13	41%	69%	74%	61%	39%	83%	22%	58%	54%
s14	32%	62%	74%	63%	36%	76%	15%	44%	38%
Average	32%	62%	74%	67%	33%	70%	13%	46%	43%
SD	0.103568	0.094811	0.136495	0.114674	0.121369	0.104945	0.055317	0.059371	0.061405

2.4.3.2 Pupillometry in late 4 s

Similar to the previous part, in this part, we also compared the data labeled by parameter setting and data based on self-assessment following formula from **formula (1)** and **(2)**. Here I compared the error rate which can be seen in **Table 8** and difference recognition in **Table 9**. The table which has grey shading shown the optimum value of error rate and difference recognition.

Table 8. Error rate in pupillometry parameter setting

	Parameter setting **1**	Parameter setting **2**	Parameter setting **3**	Parameter setting **4**	Parameter setting **5**	Parameter setting **6**	Parameter setting **7**	Parameter setting **8**	Parameter setting **9**
s1	37%	51%	64%	50%	22%	69%	51%	32%	29%
s2	27%	39%	61%	44%	12%	51%	39%	24%	18%
s3	18%	34%	46%	37%	9%	49%	34%	12%	7%
s4	41%	47%	59%	49%	20%	65%	47%	39%	33%
s5	38%	53%	69%	56%	14%	67%	53%	34%	30%
s6	33%	54%	79%	74%	1%	59%	54%	29%	23%
s7	44%	67%	87%	83%	3%	71%	67%	39%	32%
s8	27%	49%	80%	69%	0%	51%	49%	23%	18%
s9	35%	55%	84%	74%	10%	61%	55%	29%	22%
s10	46%	58%	77%	63%	30%	74%	58%	42%	36%
s11	6%	12%	20%	9%	27%	29%	12%	8%	17%
s12	45%	78%	91%	87%	3%	81%	78%	37%	19%
s13	42%	53%	66%	51%	31%	74%	53%	40%	36%
s14	38%	58%	68%	55%	22%	74%	58%	36%	28%
Average	34%	51%	68%	57%	14%	62%	51%	30%	25%
SD	0.109541	0.148534	0.178121	0.195941	0.104326	0.132898	0.148534	0.100278	0.082621

Table 9. Difference recognition in pupillometry parameter setting

	Parameter setting **1**	Parameter setting **2**	Parameter setting **3**	Parameter setting **4**	Parameter setting **5**	Parameter setting **6**	Parameter setting **7**	Parameter setting **8**	Parameter setting **9**
s1	52%	61%	70%	62%	35%	73%	18%	47%	47%
s2	39%	48%	67%	67%	27%	55%	11%	36%	33%
s3	47%	51%	58%	53%	46%	55%	14%	45%	45%
s4	51%	54%	63%	56%	48%	68%	18%	49%	47%
s5	56%	64%	76%	64%	37%	73%	13%	54%	51%
s6	46%	59%	82%	77%	24%	63%	5%	43%	38%
s7	50%	69%	87%	83%	14%	73%	4%	46%	39%
s8	44%	63%	83%	74%	24%	63%	2%	43%	39%
s9	46%	61%	86%	77%	23%	66%	6%	41%	35%
s10	51%	63%	78%	65%	36%	77%	16%	47%	41%
s11	33%	32%	35%	40%	58%	37%	17%	36%	36%
s12	48%	78%	91%	87%	12%	81%	3%	43%	27%
s13	58%	67%	74%	63%	39%	78%	21%	57%	52%
s14	48%	64%	72%	61%	37%	77%	16%	46%	40%
Average	48%	60%	73%	66%	33%	67%	12%	45%	41%
SD	0.062537	0.106205	0.139054	0.120541	0.125407	0.115451	0.0622	0.056568	0.068209

2.5 Discussion

Dewan et al, 2019 on their review article about engagement detection in online learning, mentioned that self-reporting (self-assessment) provides some useful information regarding learner engagement. This method depends on several factors are outside of the control of the researcher, such as learner's honesty, willingness to report their emotions and the accuracy of learners' perception about what they felt. Another method such as observational also has some limitations such as the observation metric that may not always be related to engagement but tend to measure compliance and willingness to adhere to rules rather than engagement. Which this statement they quoted from Whitehill et al, 2014. They mentioned very short response times on easy questions indicates that the learners are not engaged and are simply giving random answers without effort. On the other hand, our research proposed a new solution for this detection. Dewan et al, 2019, also mentioned method by using physiological data such as eye movement, neurological data tend to not interrupt learners in the engagement detection process. To do so, I try to compare the data from 3 methods of engagement or attention levels such as behavior, observation, and objective performance. And from those data, I found the difference evaluation between self-assessment and objective behavior and observations are less than 21%.

Because in my study the cognitive tasks have several levels, I investigated the effect of my task design toward pupillometry during high attention. I only analyze high attention in each task because mostly data from self-assessment fill high attention, so data in low attention could not be used. I did ANOVA analysis on 13 participants from the data that has been used in this study (14 participants), one participant ass excluded because, in one task condition, the participants' self-assessment mentioned that participants only feel low attention. I got F=0.13754, P-value 0.871978 in arithmetic in 4 digits, 5 digits 6 digits. Forward digit span F=0.16545, P-value 0.848148. Backward digit span F=0.056075, P-value 0.94555. There is no significant difference in each task with $P > 0.05$ similar to my previous publication (Zennifa et al, 2018). This could happen because even though my task contains multiple levels, the level did not need different effort and easy to be done. Other researcher mentioned that after 6 digit span, adult pupillometry continue to dilate and children begin to constrict. (Johnson et al., 2014). **Figure 12** showed the pupillometry activity in each task.

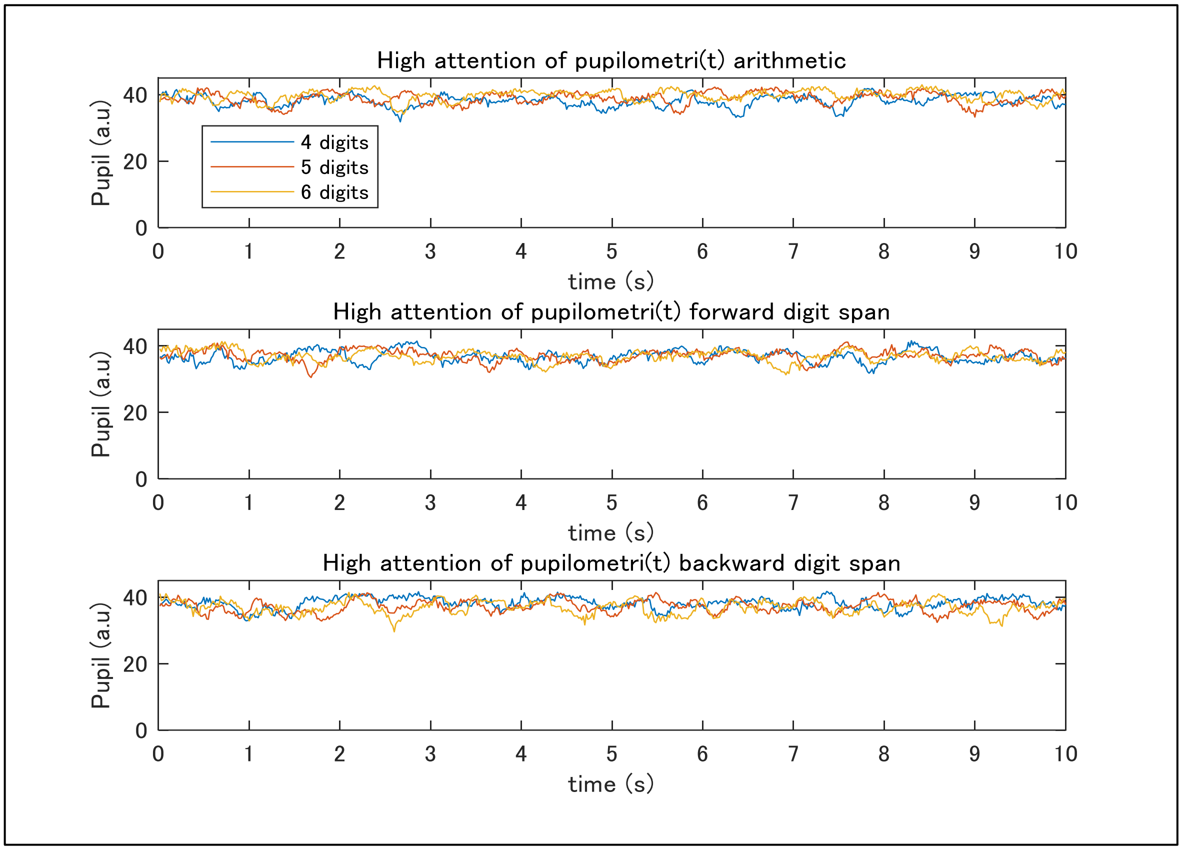


Figure 12. Pupillometry activity based on tasks (one participant)

I investigated attention gaze maps from all participants during experiments and generated the figure by Ogama (Voßkühler, A., (2009). I decided to not use gaze position in further data analysis for attention level evaluation because all participants look at the center of the monitor as showed in **Figure 13**. It has also happened because my stimulus has been appeared in the center of the monitor. So, investigating attention states based on gaze position is inappropriate in this study.

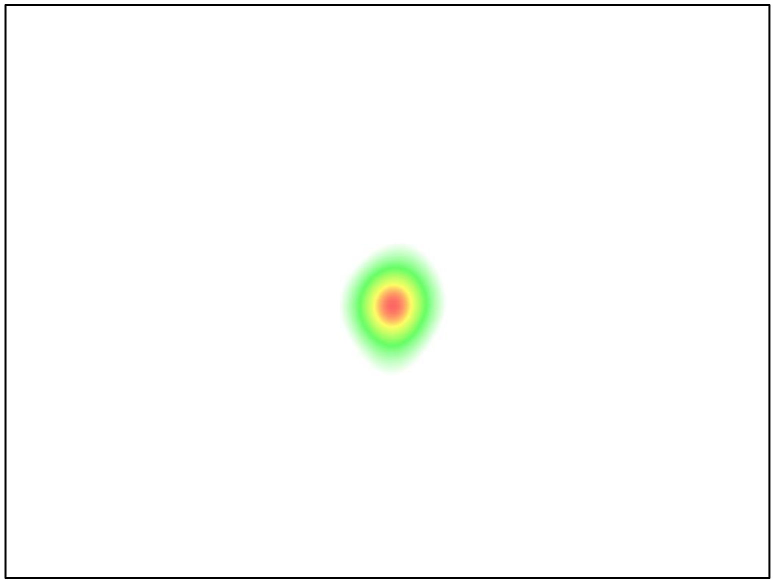


Figure 13. Heat map of the gaze attention from all participants analyzed by using the Ogama unit in pixel.

In my experiment, the encoding time is 10 seconds. Experiment for attention with encoding time at least 10 seconds also practiced by another researcher (Langner *et al, 2013*). They mentioned that 10 s become the cut off a rather conservative choice and roughly considered as sustained allocation of attention. In our study, 10 s encoding time has been also chosen because this data will be used as data labeling for EEG, ECG, NIRS which ECG features commonly can be analyzed at least in 10 s.

Even though my eye tracking system has frequency sampling up to 60 Hz, the pupil size still can be analyzed. Other research compares the ability of eye tracking with other and higher frequency sampling, it is still reliable for pupillometry (Dalmeijer, 2014), EOG records eye movements by measuring electrical potential differences between two electrodes. This takes advantage of the fact that the human eye is an electrical dipole consisting of a positively charged cornea and a negatively charged retina, first discovered by Schott in 1922 (Anina et al 2016;). So, distinguish is it blinks cause sleepiness or because of attention.

Blinks last from 80 ms to 500 ms. If eyelid closure were bigger than 500 ms it is considered as microsleep episodes (Benedetto et al, 2014).

In my study, I analyzed pupillometry in the temporal analysis. My research showed that pupillometry is higher on high attention rather than low attention. (Kang et al 2014), mentioned that pupil dilations are capable of indexing information changes independent of low-level visual changes (luminance). They proved that the change of pupil dilation is not only because of the change of light but also because of the change in information. (Hartmann et al, 2014, Naber et al, 2013) Introduced pupillometry could reflect visual attention. So, the phenomena of changing activities in my study, it also could be because of the attention activities.

Specifically, my research showed that the last 4 second has significantly different. This could have happened because pupillometry is a correlation with a temporal event. Winn et al (Winn et al, 2018) mentioned that timing is an essential part of understanding listening effort because speech demands rapid auditory encoding as well as cognitive processing distributed over time, rather than being deployed all at once at the end of a stimulus. The effort might not be uniformly distributed over a perceptual event, and pupillometry measures have the benefit of showing a change in dilation at different time landmarks. In a study conducted by (Koenig, Uengoer, et al 2017), there was increased pupil dilation in early stages of attention to consistently reinforced learning cues, while in later stages of learning when those cues did not demand as much attention, relatively larger pupil dilations were observed for ambiguous or unreinforced cues. The pupillary response was associated with a strategic shift in attention in a goal-directed task. Karatekin, Couperous, and Marcus (2004) measured significantly larger pupil dilations in conditions of divided attention in a dual-task experiment conducted to distinguish performance accuracy and efficiency (stated as "the costs of that performance in the mental effort").

Generally, blink will appear in an interval of 2–10 seconds and actual rates vary by individual averaging around 10 blinks per minute in a laboratory setting. However, when the eyes are focused on an object for an extended time, such as when reading, the rate of blinking decreases to about 3 to 4 times per minute (Bentivoglio et al., 2004). They measured the normal blink rate variations with behavioral tasks in 150 healthy volunteers, they found that blink rates during conversation are higher than resting and higher than reading. Blink rates higher in resting rather than reading was also reported by Paprocki et al, 2017. In their conclusion, they mentioned that eye blinks are connected to the higher cognitive process, so blink rates could be used as a marker of dopa- and gabaminergic functioning. In the beginning of my study, I hypothesized the difference of blink rates toward attention level can be distinguished. But unfortunately, I did not find significant difference of blink rates data. I suspected it happened because the trials time in this study is too short to make blink rates has significant difference.

In my knowledge, this study is the first study that tries to find the parameter setting of pupillometry to be used for attention level evaluation. The background of this study is because there is no explanation of former study (Zennifa et al 2018) of the usage parameter settings in pupillometry if Z score bigger than 0 and blink rates Z score lower than 0 will be labeled as high attention and low attention is the opposite way. So, I continue to investigate how to find the explanation of parameter settings in attention level evaluation by using eyetracking information. Extended study (Zennifa et al 2019) tried to developed quantitative algorithm of blink rates and pupillometry for labelling method in supervised machine learning. But in the end, I consider to not use blink rates as parameter setting because there is no significant difference in 10 second. Other pupillometry research in attention (Karatekin et al., 2007; Tsukahara et al., 2016; Hartmann et al, 2014; Geva et al., 2013; Unsworth et al., 2017 a&b; Piquado et al., 2010) did not investigate the threshold for attention level but just investigate the effect of attention and cognitive toward pupillometry. I used self-assessment to validating our data after investigating the error rate and difference recognition compare with other attention level evaluation methods (Objective performance, an observation in which the result of error rate is less than 21%. Based on my comparison, I found that threshold with z-score within a specific range ($-0.965 \leq$ pupil ≤ 1.014) as high attention.

2.6 Conclusion

In this chapter, I compared the self-assessment method with other attention level detection methods (observation and objective performance) to check the difference value of evaluation on those methods. I got a different error of self-assessment compared with other methods lower than 21%. After that, I investigated the effect of attention level based on self-assessment to blink rates and pupillometry. I found that pupillometry in low attention is smaller than high attention, especially in the last 4 seconds. I extracted the pupillometry activity in the last 4 seconds and 10 seconds into 9 algorithms each. After doing several experimental procedures, I chose parameter setting with a percentage of error of less than 15% and a different error 35 % compare with self-assessment as future labeling method.

Parameter setting which has been selected is when z-score within a specific range ($-0.965 \leq$ pupil ≤ 1.014) as high attention, other that range, will be classified as low attention.

Chapter 3. Application of new labeling in EEG-ECG-NIRS

3.1. Abstract

In this chapter, I introduce the implementation of new labelling method in a low-density hybrid system for attention level evaluation. I used a two-electrode wireless EEG, a wireless ECG, and a NIRS with two wireless channels to measure attention level during during backward digit span, forward digit span and arithmetic. High attention will be labelled to data which has pupillometry z-score within specific range ($-0.965 \leq$ pupil ≤ 1.014) and another that range, will be classified as low attention.

By using CFS+kNN algorithm, my result showed the accuracy system of EEG-ECG-NIRS (83.33± 5.95%) has the highest accuracy compare with EEG (81.90± 4.69%), ECG (82.51±3.57%), NIRS (78.37±7.12%). Algorithm CFS+kNN also shown highest performance compare with other methods such as CFS+SVM (55.49± 27.89%), kNN (80.84± 3.88%) and SVM (55.88± 13.14%).

3.2 Materials and method

3.2.1 Participants

In my experiment, 24 participants were Kyushu University students, with ages ranging from 21 to 28 (24.25 ± 2.3). All participants had a normal visual function and were free of disability. Among them, 21 were right-handed, one participant was ambidextrous, and two participants were left-handed. The participants were instructed not to consume any caffeine 2 hours before the experiment because it could affect the HRV (Martínez-Sellés et al, 2013; Oliveira et al, 2017). The study was conducted following the ethical principles of

Kyushu University and the Declaration of Helsinki. Written informed consent was obtained from each participant before the experiment as showed on **Appendix 2**.

3.2.2 Experiment task

The experiment was done at between 10:30 am and 1:30 pm in a dimly lit room. We also recorded the behavior activities of the participants using a webcam camera (Logicool C270, Logitech, city, Switzerland), put in front of the participant's face.

Three types of attention tasks were used: a backward digit span (BDS) (Jensen et al., 1975; Cullum., 1998; Berka et al 2007; Zennifa et al., 2018; Zennifa et al., 2019; Rosenthal et al, 2006), a forward digit span (FDS) (Jensen et al., 1975; Cullum., 1998; Berka et al 2007, Zennifa et al., 2018; Zennifa et al., 2019; Rosenthal et al, 2006), and an arithmetic (Zennifa et al, 2018). These tasks consist of three levels. Level one consisted of a series of 30 sets of four digits, level two: 30 sets of five digits and level three: six digits. Most of the questions in this experiment were relatively simple and did not require any prerequisite knowledge or specific skills. However, a good level of attention and alertness was required to avoid making easy mistakes because the response time was limited to 20 s. Each trial started with the presentation of a central, white fixation dot on a dark background until the participant's eyes could be accepted by the eye tracker. Next, cognitive questions (i.e., encoding session) would appear for 10 s and the participant was instructed to respond within 20 s. All cognitive tasks were counterbalanced. The measurement of EEG-ECG-NIRS-EOG and Eye tracking was recorded after the practice session finished.

3.2.2.1 BDS (Backward Digit Span)

In this task, every beginning of the task, participants will be asked to look at the dot point. When eye tracking can detect the eye's position, there will be several digits appear continuously. Digits will appear every 2.5 seconds in 4 digit level, 2 seconds in 5 digit level and 1.67 seconds at 6 digit level. After that participant were asked to type the digits backward in reverse order. The maximum time to be given in the answer session is up to 20 seconds. Following that there will be a message that informed participants the answer is recorded. The task can be seen in **Figure 14**.

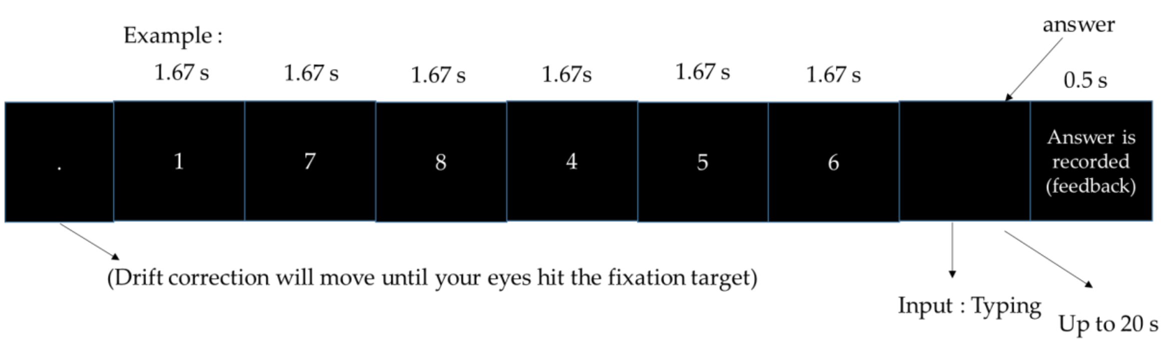


Figure 14.Digit span.

3.2.2.2 FDS (Forward Digit Span)

In forward digit span, task design is similar like a backward digit span (BDS), but in this session, the participant is asked to type the digits in the forward order.

3.2.2.3. Arithmetic

For the arithmetic task, after participants' eyes can be detected by eye tracking during looking at dot points. There will be digits following letters that appear continuously. Digits and letters will appear every 2.5 seconds in 4 digit level, 2 seconds in 5 digit level and 1.67 seconds at 6 digit level. The participants were asked to calculate operations using just the number. The question would appear together with the blank forms, and the participants were asked to type the answer within 20 s. The task can be seen in **Figure 15.**

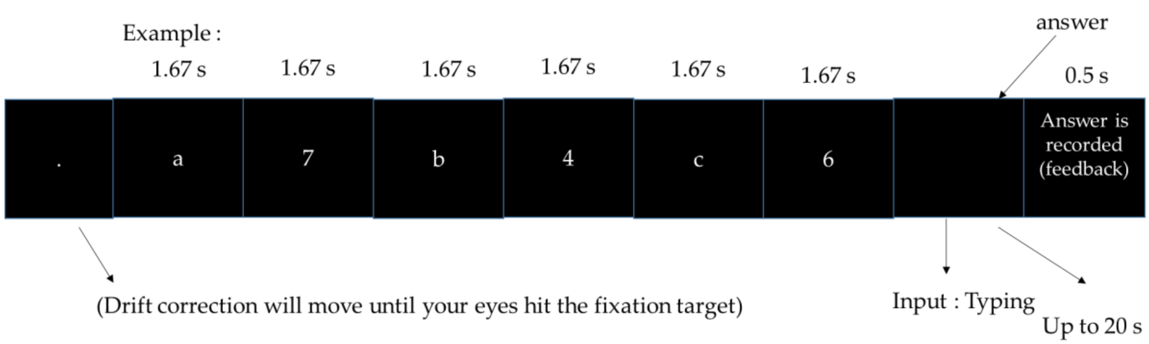


Figure 15. Arithmetic

3.2.3. Software and Apparatus

Stimuli were presented on a 17-inch CRT monitor (1024 × 768) using OpenSesame (Mathôt et al, 2012), using the legacy back-end for the display control and the PyGaze toolbox (Dalmaijer, 2014) for the eye tracker.

3.2.3.1. Eye Tracking

Before the start of each task, participants were positioned in front of an eye tracker (The EyeTribe tracker version 1, Copenhagen, Denmark). The distance of the participants' eyes from The EyeTribe was estimated to be ~57 cm. The participants were asked to fix their heads on a chin rest. Eight participants were successfully calibrated in the 60 Hz mode while three participants were successfully calibrated in the 30 Hz mode. In this study, we calibrated and validated the eye tracking system to each participant using a nine-point dot matrix. After validation, the eye tracker that had been embedded with the OpenSesame software labeled each calibration point with the error in the degree of the visual angle between the calibrated and validated measures. If the calibration points do not exceed 1°[deg] and the greatest single point error does not exceed 1°, the process would continue. Before each trial, a one-point eye tracker recalibration was performed.

3.2.3.2. Electrophysiology

In this study, EEG, and ECG (Polymate Mini AP 108, Miyuki Giken Co., Ltd., Kasugai-city, Japan) signals were sent by Bluetooth to a computer. The frequency of sampling was 500 Hz. To evaluate attention level during a cognitive task, we recorded EEG at the Fz and Pz, referenced at A1. These areas are highly correlated in cognitive activities (Culham et al., 2006; Reynolds et al., 2016; Chayer et al., 2001). The ECG was recorded on the chest (2-lead placement) (Stikic at al., 2014;, Zennifa et al.,2015; Iramina et al., 2010). We chose this position for the ECG to reduce the effect of artifact movements when the participant responded to the tasks. We also put two electrodes for a vertical EOG as shown in. **Figure 16** shows the electrode placements. This location was chosen to detect blink (Waters et al.,2005 ; Huang et al, .2018).

3.2.3.3. Near-Infrared Spectroscopy

As shown in **Figure 16**, a spatially resolved continuous-wave NIRS system (PocketNIRS; DynaSense Inc., Hamamasu, Japan) was placed symmetrically to measure hemodynamic activity from the prefrontal region (Fp1 and Fp2). A black tensor bandage was wrapped around the subject's head to prevent light from entering the sensors. The NIRS signal was sent via Bluetooth to the computer. This NIRS had wavelengths of 735, 810, and 850 nm. The frequency sampling was 10.2 Hz. The NIRS position is shown in **Figure 16.**

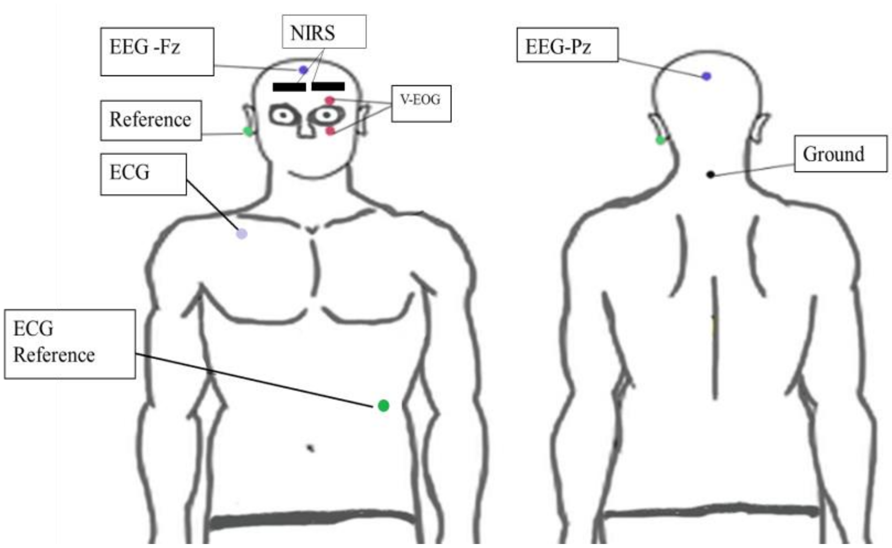


Figure 16. Hybrid system placement: EEG (Fz and Pz), ECG (2-lead placement), NIRS (Fp1 and Fp2).

3.3 Analysis for New Labelling of Attention Level Detection in EEG-ECG-NIRS

During the answer session, the participants would shift their gaze to the keyboard. This condition would also cause an artifact movement of the eyes and EEG-ECG-NIRS. So, to ensure high-quality data, I only analyzed the encoding session. The details of my analysis design are as follows.

3.3.1 Data Preprocessing

3.3.1.1 Attention Level labeling

In this thesis, I adapted a supervised learning method, which made data labeling a crucial part of the definition. Data labeling in this study was my purposed parameter setting. If the Z-score of the pupillometry within range (1.014) to (-0.965) I labeled the data point as high attention other will be labelled as low attention.

3.3.1.2. Feature Extraction

This study used a multimodal system (EEG-ECG-NIRS) where the signal characteristic can be seen in **Figure 17**. I extracted those multimodal signals into 59 features in this study (i.e., 34 features from EEG, 7 features from ECG, and 18 features from NIRS).

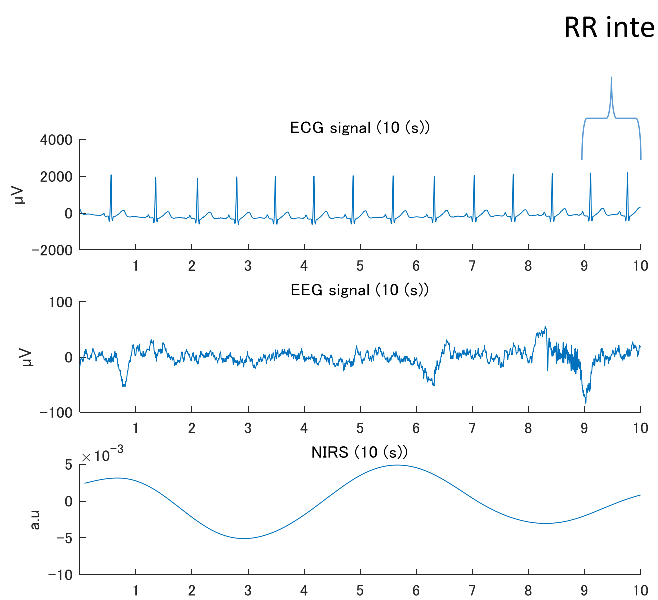


Figure 17 EEG-ECG-NIRS signal during the task load of one subject in one trial.

3.3.1.2.1 EEG Feature Extraction

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from the scalp. **Figure 18 shows t**he recorded waveforms in 10 second based on my task design. EEG analysis can be done by using linear domain and nonlinear domain. In this study, I extracted 34 features of EEG (Linear and nonlinear domain).

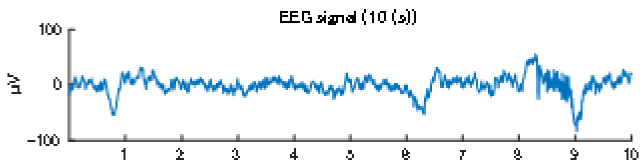


Figure 18. EEG wave activities in 10 seconds

From the linear parameters, I used the Hjorth parameter to investigate the variety of EEG signals. As can been seen in equation (5), (6) and (7), (y(t)) is the symbol of EEG signals in time domain that I used to calculate activity, mobility and signals complexity. The Hjorth parameter has been used in several EEG studies (Li et al., 2018;, Akar et al.,2016; Hall et al., 2009). Mostly it was used because this parameter is of minimal complexity and calculated in real-time.

$$\mathrm{activity} = \mathrm{var}\big(\mathrm{y(t)}\big) \qquad (5)$$

$$\mathrm{mobility} = \sqrt{\frac{\mathrm{var}(\frac{\mathrm{d_y(t)}}{\mathrm{dt}})}{\mathrm{var(y(t))}}} \qquad (6)$$

$$\mathrm{complexity} = \frac{Mobility(\frac{d_y(t)}{dt}}{mobility(y(t))} \qquad (7)$$

I also used Kolmogorov complexity to extract EEG in linear domain. Kolmogorov is a method to calculate signal complexity based on the signal dimension (Kolmogorov, 1965;

Lui et al., 2015). Where φ represents a universal computer, p represents a program and x represent a string. I extracted Kolmogorov complexity by using library which provided in mat lab (Faul, s 2015).

$$K_{\varphi}(x) = \{min_{\varphi(p)=x} l(p)\} \quad (8)$$

The EEG signal was calculated in 10 s windows. Wavelet Daubechies 8 was applied to get the value of power spectral density. Because I used 500 Hz frequency sampling EEG, I need to decide the decomposition level wavelet. By following the Nyquist rule, half the frequencies should be removed. Low pass filter *g* and high pass filter *h* with half cut off frequency. **Figure 19** shows wavelet transform decomposition which seven levels.

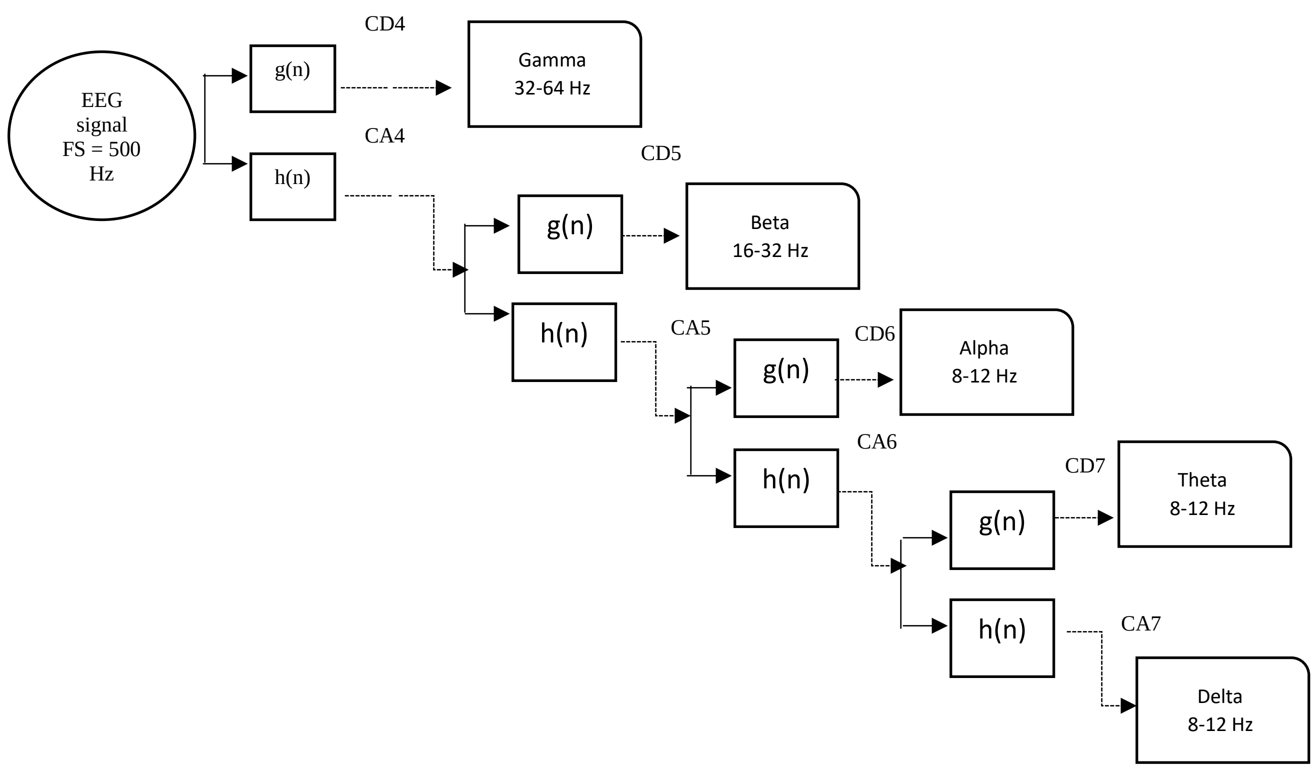


Figure 19. Seven levels EEG signal decomposition using discrete wavelet transform.

After obtaining the power of the EEG oscillation, I also calculated the maximum power of EEG and power density integral of EEG which can be seen in **appendix 6**. Also the relative power of each band (i.e., theta (θ) (Equation (13)), alpha (Equation (14)), and beta (β), (Equation (15), and gamma (γ) (Equation (16)) were computed from each electrode as this following equations:

power θ = ((D7.^2))/length(D7); (9)

power α = ((D6.^2))/length(D6); (10)

power β = ((D5.^2))/length(D5); (11)

power γ = ((D4.^2))/length(D4); (12)

Relative θ = (power θ)/(power θ + power α + power β + power γ) (13)

Relative α = (power α)/(power θ + power α + power β + power γ) (14)

Relative β = (power β)/(power θ + power α + power β + power γ) (15)

Relative γ = (power γ)/(power θ + power α + power β + power γ) (16)

I calculated EEG power spectral entropy after calculated EEG power spectral density by using pwelch function from Matlab library and applied entropy calculation by using Matlab library **Appendix 6**. The calculation is based on Shannon formula (**equation 17)** I calculated power spectral entropy to investigated correlation nonlinear features toward attention level.

$$SE_n = -k \sum_{f=0.5}^{f=45} \widehat{Psd}(f) log \widehat{Psd}(f) \quad (17)$$

Where k=1 and the basis f log is 10. The symbol of f means frequency, and the frequency was to be set in range 0.5 Hz to 45 Hz.

3.3.1.2.2 ECG Feature Extraction

There are three main components to an ECG: the P wave, which represents the depolarization of the atria; the QRS complex, which represents the depolarization of the ventricles; and the T wave, which represents the repolarization of the ventricles (Lily, 2016). I extracted 7 features from ECG signals (Linear and nonlinear domain). Figure 20 shows the ECG characteristic in 10 second during my experiment.

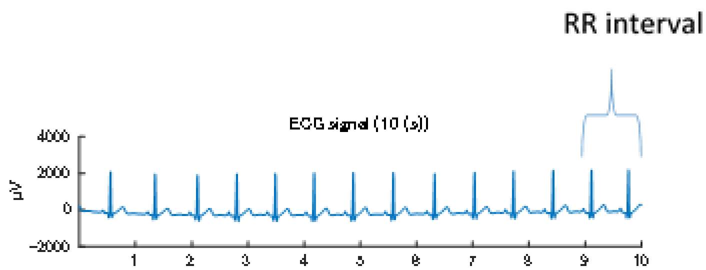


Figure 20. ECG signals in 10 seconds

I calculated the change of RR interval of the ECG for every 10 s window. Then, I calculated the value of HRV activity by using a fast Fourier transform. In this study, I calculated the high frequency (HF) ECG component to measure the level of parasympathetic nerve activity in the autonomic nervous system. The HF component can be found from 0.15 to 0.4 Hz. Heart rate (HR) was also calculated, using Equation **(18)**. The maximum power spectral density and power density integral were calculated after obtaining the value of the power spectral density:

$$HR = 60/((\text{median}(\text{RR interval}))/(\text{frequency sampling})) \quad (18)$$

I calculated the spectral entropy from EEG and ECG data in a nonlinear domain. Script code can be seen in **appendix 6**. Similar like EEG analysis, I calculated ECG signal entropy after calculated power spectral density of signal by using pwelch function and applied entropy calculation based on **equation 18**. I also calculated the Hjorth parameter of ECG signals with the same equation 5, 6, 7 and Kolmogorov equation based on equation 8.

3.3.1.2.3 NIRS Feature Extraction

Near infrared spectroscopy (NIRS) signals also measured in this study. NIRS is used to calculate the hemodynamic activity of the brain. Compare with ECG and ECG, NIRS has slower frequency as can be seen on **figure 21**.

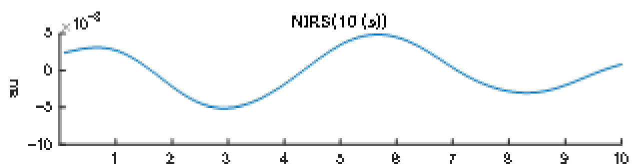


Figure 21. NIRS signals in 10 second

In this study, I extracted 18 features of NIRS signals in time domain analysis by using hjorth parameter formula which can be seen bellow:

$$\mathrm{activity} = \mathrm{var}\big(\mathrm{y(t)}\big) \qquad (19)$$

$$\mathrm{mobility} = \sqrt{\frac{\mathrm{var}(\frac{\mathrm{d_y(t)}}{\mathrm{dt}})}{\mathrm{var(y(t))}}} \qquad (20)$$

$$\mathrm{complexity} = \frac{Mobility(\frac{d_y(t)}{dt}}{mobility(y(t))} \qquad (21)$$

This hjorth formula also is similar formula which has been applied for EEG and ECG signals.

Table 10. Feature types from all signals.

Feature Type	Extracted Features
Time-frequency domain features	• Hjorth parameter: Activity (EEG, ECG, NIRS) • Hjorth parameter: Mobility (EEG, ECG, NIRS) • Hjorth parameter: Complexity (EEG, ECG, NIRS) • Kolmogorov complexity (EEG, ECG) • Maximum power spectral alpha (EEG) • Maximum power spectral theta (EEG) • Maximum power spectral beta (EEG) • Maximum power spectral gamma (EEG) • Power density integral alpha (EEG) • Power density integral theta (EEG) • Power density integral beta (EEG) • Power density integral gamma (EEG) • Relative power alpha (EEG) • Relative power theta (EEG) • Relative power beta (EEG) • Relative power gamma (EEG) • Heartrate (ECG) • HF (High-frequency value from heart rate variability (ECG))
Nonlinear domain feature	• Spectral entropy (EEG, ECG)

3.3.1.3. Predictive Modeling in Machine learning

There are many ways to develop automatic detection. Some popular methods are machine learning (Obermeyer and Emanuel., 2016; Tao et al., 2019), expert system (Gholami et al., 2012; Zennifa et al., 2014), deep learning (Wang et al., 2018; Yuan et al., 2019). Generally, there are two main tasks in machine learning. They are unsupervised and supervised machine learning (Russel et al., 2010). The main difference between the two types is that supervised learning is done by data labeling and the goal is to learn a function that given a sample of data and desired output. Supervised machine learning is a method in machine learning by using knowing labeling methods to label the data and has the expecting result (input-output pairs) (Stuart et al, 2010). On the contrary, unsupervised machine learning is not based on data labeling and its goal is to infer the natural structure present within a set of data points. Measuring human mental states based on physiological activity has also been investigated by integrating EEG and ECG features (Stikic et al., 2014). The unsupervised method has been applied for cognitive state recognition in that experiment. However, the unsupervised learning requires large amounts of data to get an appropriate pattern. Moreover, there is no method to validate the data. In our study, data labeling relied on physiological activities. I used Weka 3.8 (Hall et al., 2009) data mining for machine learning.

3.3.1.3.1 CFS (Correlation Based Feature selection)

The feature selector is important for reducing the time needed to find the best features to be used in a study case (Aghajani et al., 2017; Hall et al, 1999), and it also can increase the accuracy of classification. The CFS (correlation-based feature selection) is a simple filter algorithm that ranks feature subsets according to a correlation-based heuristic evaluation function (Hall, 1999). This feature selector calculates features that are highly correlated with the class and uncorrelated with each other. Irrelevant features would be ignored because they have a low correlation with the class. Redundant features would be screened out, as they are highly correlated with one or more of the remaining features. The acceptance of a feature will depend on the extent to which it predicts classes in an area if the instance space was not already predicted by other features. Equations (18) through (21) show the calculation process:

$$r_{cf} = \frac{\sum cf_i cf_j}{\sqrt{\sum cf_i^2 \sum cf_j^2}} \quad (22)$$

$$r_{ff} = \frac{\sum f_{if_j}}{\sqrt{\sum f_i^2 \sum f_j^2}} \quad (23)$$

$$M_s = \frac{k\overline{r_{cf}}}{\sqrt{k+k(k-1)\overline{r_{ff}}}} \quad (24)$$

$$\mathrm{CFS} = \max_{s}\left[\frac{r_{cf_1}+r_{cf_2}+\cdots+r_{cf_k}}{\sqrt{k+2(r_{f_1f_2}+\cdots+r_{f_if_j}+\cdots+r_{f_kf_1})}}\right] \quad (25)$$

M_s = the correlation between the summed features (k) and the outside variable.

$\overline{r_{cf}}$ = Average of the correlation between the features class.

$\overline{r_{ff}}$ = Average inter-correlation between features-features.

k = Number features in the dataset

CFS = correlation feature selector

Based on the explanation from Hall PhD Thesis (**Hall., 1999)**, **Equation 25** formed the core of the CFS algorithm and imposes a ranking on features subsets in all possible feature subsets. Similar to his thesis, my study also applied the "Best first" method as searching space and we can start with either no features or all features. Preventing the best-first search algorithm from exploring the entire feature subset search space, a stopping criterion is imposed regarding Hall explanation on his PhD thesis. The search method will terminate if expanded subsets showed no improvement over the current best subset. In this study, I used WEKA data mining software to applied CFS. For further understanding, I created a dataset based on Hall PhD thesis that can be seen on **Table 11** and **Table 12.**

Table 11. Dataset example

Instance	Features				Class
	A	**B**	**C**	**D**	
1	0.03	0.5	0.0009	0.0876	X
2	0.03	0.5	0.0009	0.5	X
3	0.004	0.5	0.0009	0.0876	Y
4	0.1	0.06	0.0009	0.0876	Y
5	0.1	0.07	0.123	0.0876	Y
6	0.1	0.07	0.123	0.5	X
7	0.004	0.07	0.123	0.5	Y
8	0.03	0.06	0.0009	0.0876	X
9	0.03	0.07	0.123	0.0876	Y
10	0.1	0.06	0.123	0.0876	Y
11	0.003	0.06	0.123	0.5	Y
12	0.004	0.06	0.0009	0.5	Y
13	0.004	0.5	0.123	0.0876	Y
14	0.1	0.06	0.0009	0.5	X

There are 4 features, 14 instances and 2 classes to be created in **Table 11.** After that we calculated correlation in $\overline{r_{cf}}$ and $\overline{r_{ff}}$ based on **Equation 18 and 19.** Then I calculated the CFS value based on **Equation 25.** From those calculation, as can be seen on **Table 12,** features which highest correlation will be selected as the future features. In this case, features [**a]** and [**c]** are used as selected features.

Table 12. Example of feature selection based on Formula (CFS)

Feature set	K	$\overline{r_{cf}}$	$\overline{r_{ff}}$	Merit
[]	0	-	-	$\frac{0}{\sqrt{0+0(0-1)0}} = 0.0$
[a]	1	0.13	1	$\frac{1x0.13}{\sqrt{1+1(1-1)1}} = 0.13$
[b]	1	0.025	1	$\frac{1x0.025}{\sqrt{1+1(1-1)1}} = 0.25$
[c]	1	0.185	1	$\frac{1x0.185}{\sqrt{1+1(1-1)1}} = 0.185$
[d]	1	0.081	1	$\frac{1x0.081}{\sqrt{1+1(1-1)1}} = 0.081$
[a c]	2	0.158	0.022	$\frac{2x0.158}{\sqrt{2+2(2-1)0.022}} = 0.22$
[b c]	2	0.105	0.258	$\frac{2x0.105}{\sqrt{2+2(2-1)0.258}} = 0.133$
[c d]	2	0.133	0	$\frac{2x0.133}{\sqrt{2+2(2-1)0}} = 0.188$
[a b c]	3	0.113	0.132	$\frac{3x0.113}{\sqrt{3+3(3-1)132}} = 0.175$
[a c d]	3	0.132	0.0096	$\frac{3x0.132}{\sqrt{3+3(3-1)0.0096}} = 0.226$
[a b c d]	4	0.105	0.0718	$\frac{4x0.105}{\sqrt{4+4(4-1)0.0718}} = 0.191$

3.3.1.3.2 kNN (k Nearest Neighbor)

In this thesis, my algorithm is started by 3 multimodal input (EEG-ECG-NIRS) into one dataset. I used WEKA data mining software and applied 10 fold cross-validation and after that applied CFS processing on the next process. CFS calculates features-class and feature-feature correlations and then searches the feature subset space by using the "best first search" method. The subset with the highest correlation **(Equation 25)** found during the search. Then I applied the selected features to my training and testing data, and classify the features by using kNN (k nearest neighbor). kNN is an approach for data classification that estimates the probability that a data point belongs to one group or another, depending on the group membership of the data points nearest to it.

3.3.1.3.3 SVM (Support Vector Machine)

In this study, I used WEKA mining software and applied support vector machine (SVM) polynomial as classifier. SVM is supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis (Corinna, et al 1995). One of the effectiveness of SVM depends on the selection parameter C. C is a regularization parameter that controls the tradeoff between the achieving a low training error and a low testing error that is the ability to generalize your classifier to unseen data. Typically, each combination of parameter choices is checked using by accuracy performance.

3.3.1.3.4 Performance calculation

In this study, the accuracy of performance was calculated based on several variables, such as the true positive (TP) rate. The TP rate was calculated as the proportion of cases that were correctly classified as class high or low among all cases that are true of the same corresponding class (P), i.e., the extent to which part of the classes was captured. The TP rate value is also equivalent to the recall.

$$\text{recall} = \frac{TP}{P}$$

I also calculated the false positive (FP) rate. The FP rate is the proportion of cases that were classified as class high or low but belong to a different class, among all cases that are not of class high or low. The precision is the proportion of the cases that truly have a class low or high among all those that were classified as class high or low.

$$\text{Precision} = \frac{TP}{TP + FP}$$

The recall (i.e., sensitivity) is the fraction of relevant instances that have been retrieved over the total amount of relevant instances. The F-measure is simply twice the time value of the precision and recall divided by the sum value of precision and recall. I also investigated the area under a receiver operating curve (ROC) for our performance evaluation.

$$\text{F} = 2\,\frac{precision.recall}{precision + recall}$$

3.3.2. Data Management

3.3.2.1 Data Modelling

3.3.2.1.1 Hold out Method

In this process, data was separated into training set and testing set. The training aims to to fit the model and testing data to test the modal. In this method, Data was separated into 70% data for training, 30% data for testing.

3.3.2.1.2 Cross validation Method (XV Method)

In this process, data set is divided into k subsets, and the holdout method is repeated k times. Each time, one of the k subsets is used as the test set and the other k-1 subsets are put together to form a training set. Then the average error across all k trials is computed. In this study, the cross validation has been applied in 10 folded.

3.3.2.1.3 Leave one subject out validation (LOSOXV)

In this process, data was separated into training set and testing set. The training aims to to fit the model and testing data to test the modal. In this method, one participant is leave out as testing data and other used as training data. This process was repeated till all participants finish to be tested.

3.3.2.2. Data Balancing

3.3.2.2.1 Oversampling

In this study, high attention and low attention data are an imbalance, I need to anticipate this condition by re-sampling my data (Chicco et al, 2017). There are several ways to re-sampling data. To make my data become balance, I applied oversampling, which means increasing the number of minority class members in the training set. In this study, oversampling was performed by using weka resample library. This resample library can produces a random subsample of a dataset. The original dataset must fit entirely in memory. The number of instances in the generated dataset may be specified. The filter can be made to maintain the class distribution in the subsample, or to bias the class distribution toward a uniform distribution. When used in batch mode (i.e. in the FilteredClassifier), subsequent batches are NOT resampled. Formula to be used in this system as below :

$$sample\ size = \frac{A}{100} x \frac{(1-b)xC[i] + BxD()}{E}$$

A=Percentage of data belong to majority class

B= wheter to use bias belong to uniform class

C[i]= holds the number of instance in class i

D= Total number of instances in the dataset

E= the number of classes that actually occur in the dataset

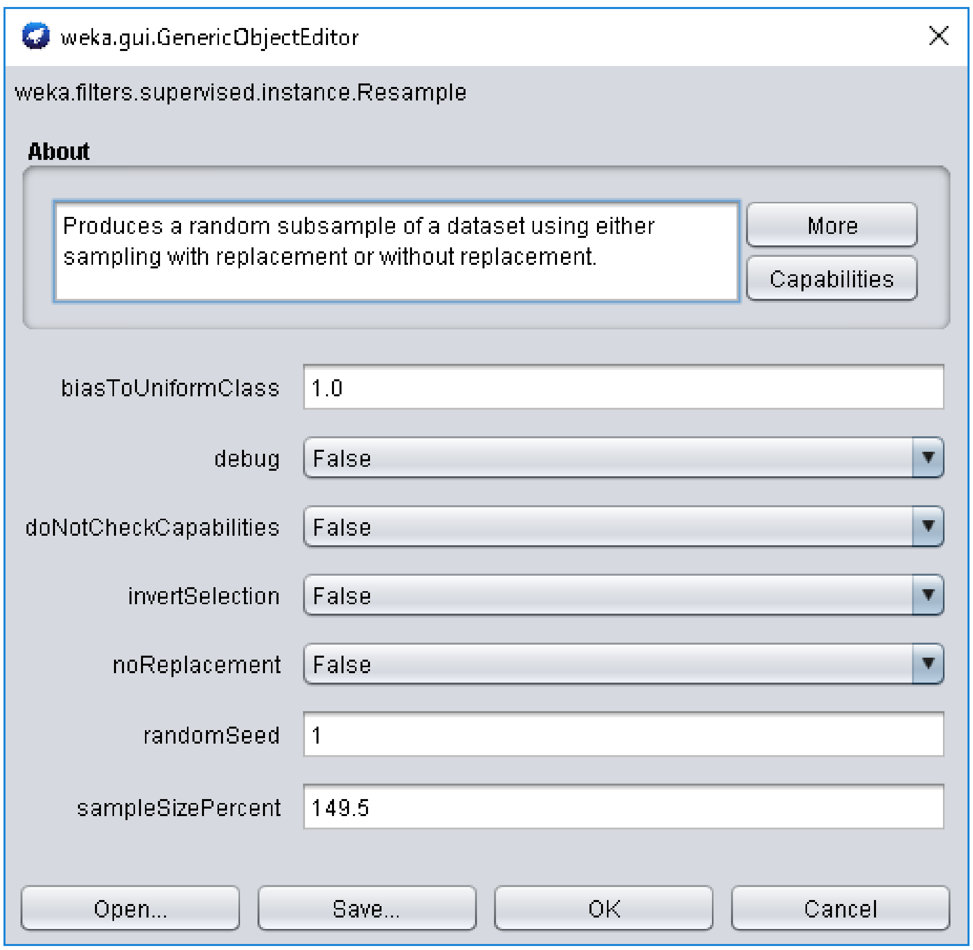


Figure 22 Example of resampling in weka

By using over-sampling there is no information from the original training set is lost since all members from the minority and majority classes are kept. (Rahman et al., 2013; Chawla et al., 2018). This process can be seen on **Figure 23**. In this study, oversampling performed by using weka.

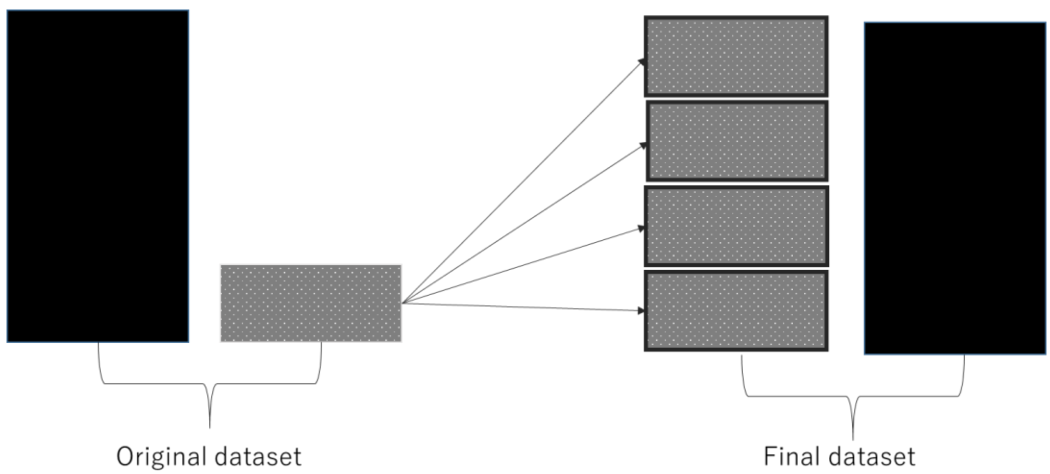


Figure 23. Oversampling process, taken the minority and duplicated it

3.3.2.2.2 Weight balancing (balance filtering)

I also tried to use balance filtering which is provided in Weka's library (Mark et al, 2009). In this technique, instead of sampling the data, I just increase the number of weight from each state. This filter reweighs the instances in the data so that each class has the same total weight. The total sum of weights across all instances will be maintained. Only the weights in the first batch of data received by this filter were changed. The balancing filter increased the weight of sample numbers for the low class and decreased the number of weight in the high class, resulting in the percentage in each class becoming 50%. This process can be seen on **Figure 24.** This study performed by using WEKA.

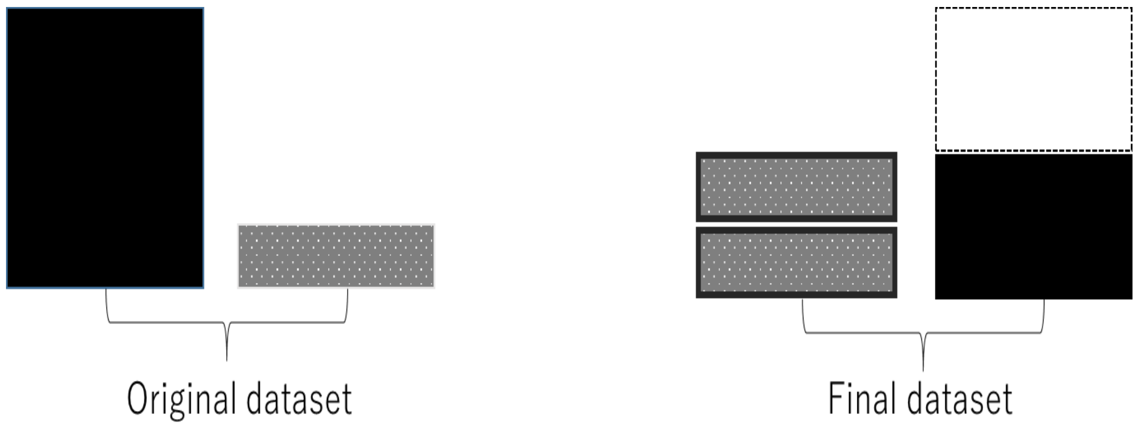


Figure 24. Weight balancing process minority is duplicated, the majority is reduced

3.4 Results

3.4.1. EEG-ECG- NIRS toward Attention Level Based on Purposed Labelling Method

In this study, due to technical problems and participant health conditions, from 24 participants, only 10 participants were analyzed in this chapter. Technical problems mostly occurred from NIRS signals. **Figure 25** is the sample of NIRS signal which Zscore (Tsunashima et al., 2012; Ichikawa et al., 2014; Yasumura et al., 2014; Blanco et al., 2018) more than 5 were excluded because of the possibility of motion artifacts. Because our systems is multimodal systems, if one participant has noisy signals, whole data of that participant will not be used.

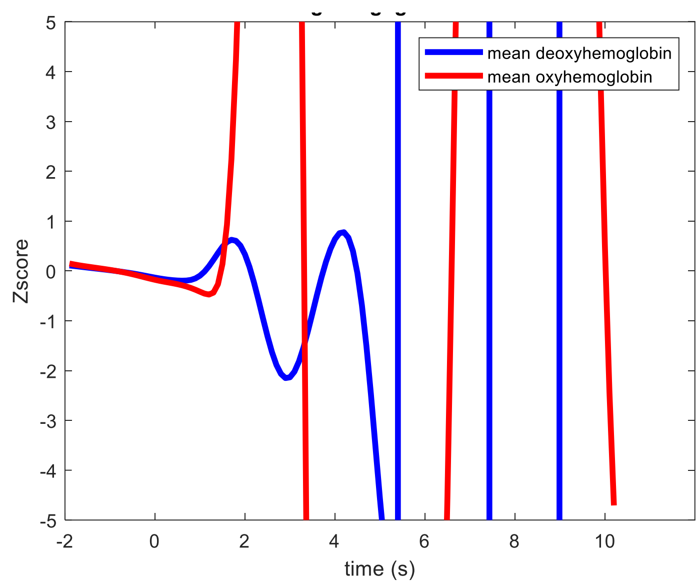


Figure 25. Example of rejected data from NIRS

In my study, I used 59 features that were extracted from EEG, ECG, NIRS signal which data labeling is labeled by using my proposed parameter settings from **Attention level labeling. Table 13** shows the activity of high attention and low attention toward EEG signals. Here I calculated the average of 1800 data points from participants without balancing the data states and applied normalization of EEG-ECG-NIRS. Normalization is applied because I considered the differences of this multimodal signals. In this table, a Red color down arrow shows the activity is decreased, and a green color up arrow shows the activity is increased. From this data, we can see that relative beta is increased during high attention and relative theta is decreased during high attention in both Fz and Pz area, on the other hand, relative beta is decreased during low attention and relative theta is increased during low attention.

3.4.2. Classification algorithm

I adopted several classifiers to approach and investigate the best verification strategy to evaluate recognition performance. I also investigated the best feature selector to decrease the time combination for finding the optimum features. The feature selection was conducted on the 1800 data point from all participants. In this study, the data of attention level can be seen in **Table 13**. From this table, the sample statistic for low attention levels is lower than the high attention level

Table 13. Data of attention level

Label	Count	Weight
High	1345	1345
Low	455	455

Because the data is imbalances, I used a weight balancing filter in weka 3.28 (Mark et al, 2009) to make the sample data balance. This filter reweights the instances in the data so that each class has the same total weight. The total sum of weights across all instances will be maintained. Only the weights in the first batch of data received by this filter are changed. The balance filter increasing the weight of sample numbers for high class and decreased the number of weight in low class. From this step, the percentage in each class became 50%. At the same time, I also tried another balancing technique called oversampling. I oversampled data from minority value (low attention) to have the same number of data like high attention. To find the highest performance algorithm, I compared several classifier and validation technique which the labelling is based on my proposed parameter settings. The result can be seen in **Table 14 and 15.**

Table 14 Classification performance over several validation methods and balancing technique kNN

oversampling	kNN, k=1	kNN, k=3	kNN, k=5	kNN, k=9	kNN, k= 13
Hold out	64.09± 14.84%	55.05±12.75%	54.86± 12.50%	56.94± 13.05%	56.32± 12.58%
10 XV	67.22± 6.13%	53.95± 10.06%	54.11± 11.09%	56.31± 12.26%	55.58± 11.74%
LOSOXV	81.63± 6.13%	70.80± 4.15%	64.78± 7.09%	61.74± 6.39%	59.92± 8.32%
Without CFS					
Hold out	64.76± 16.07%	58.04±13.05%	55.69± 12.37%	56.75± 12.13%	55.53± 11.52%
10 XV	63.96± 14.27%	56.85± 10.55%	54.84± 10.92%	56.16± 11 .44%	54.93± 10.83%
LOSOXV	79.41± 4.46%	68.31± 7.39%	63.64± 8.62%	61.40± 9.29%	59.87± 9.61%
Weight balancing	kNN, k=1	kNN, k=3	kNN, k=5	kNN, k=9	kNN, k= 13
Hold out	67.45± 15.67%	51.07± 12.25%	50.69± 12.19%	52.17± 12.75%	60.14± 15.25%
10 XV	64.08± 10.60%	52.16± 10.62%	51.11± 9.67%	53.27± 14.37%	61.52± 13.99%
LOSOXV	83.33± 5.95%	63.28± 7.84%	65.03± 9.23%	60.69± 11.18%	59.80± 10.13%
Without CFS					
Hold out	68.46± 14.33%	68.88±15.42%	72.18± 13.29%	60.11± 15.23%	60.58± 16.94%
10 XV	63.05± 11.97%	47.86±6.84%	58.25± 12.31%	59.03± 14.89%	59.66± 16.80%
LOSOXV	80.84± 3.88%	62.94±8.39%	64.36± 9.09%	59.68± 9.09%	61.20± 9.77%

Table 15. Classification performance over several validation methods and balancing technique SVM

Oversampling	SVM, c=1	SVM, c=3	SVM, c=5	SVM, c=9	SVM, c=13
Hold out	55.92± 26.70%	56.62± 26.16%	56.34± 26.13%	56.29± 26.04%	56.55± 25.82%
10 XV	55.84± 26.69%	56.52± 26.15%	56.36± 26.13%	56.24± 26.03%	56.47± 25.80%
LOSOXV	55.32± 14.83%	56.47± 14.39%	56.70± 14.18%	56.53± 14.33%	59.93± 13.98%
Without CFS					
Hold out	54.38± 28.71%	55.11± 28.31%	54.80± 28.29%	55.26± 28.23%	55.23± 28.18%
10 XV	54.27± 28.68%	55.02± 28.29%	54.69± 28.26%	55.17± 28.21%	55.16± 28.17%
LOSOXV	56.77± 14.21%	55.57± 12.95%	55.48± 12.83%	55.32± 12.81%	55.27± 12.91%
Weight balancing	SVM, c=1	SVM, c=3	SVM, c=5	SVM, c=9	SVM, c=13
Hold out	55.49± 27.89%	57.67± 26.29%	57.16± 26.37%	57.23± 26.30%	57.26± 26.42%
10 XV	56.74± 26.53%	57.45± 26.28%	57.16± 26.36%	57.05± 26.28%	57.06± 26.39%
LOSOXV	55.67± 14.36%	55.92± 14.34%	55.91± 14.34%	56.02± 14.33%	52.41± 15.11%
Without CFS					
Hold out	55.13± 27.98%	55.44± 27.96%	55.65± 27.45%	55.45± 27.76%	55.32± 27.89%
10 XV	55.01± 27.96%	55.22± 27.91%	55.44± 27.41%	55.17± 27.70%	55.07± 27.84%
LOSOXV	55.88± 13.14%	56.17± 13.28%	56.02± 13.43%	55.90± 12.83%	55.62± 12.64%

To see the superiority of EEG-ECG-NIRS (Hybrid) system towards standalone system, I compared. Table 16 showed the accuracy of EEG, ECG, NIRS and Hybrid system.

Table 16. Accuracy EEG ECG NIRS

	EEG	ECG	NIRS	HYBRID
Accuracy	81.90± 4.69%	82.51±3.57%	78.37±7.12%	83.33± 5.95%

3.5. Discussion

In this chapter, I explored a novel way of combining EEG, ECG, and NIRS with a low-density of electrodes/channels for attention level evaluation. The combination of these three different approaches is commonly termed as a hybrid system. The integration of NIRS and EEG is complementary because they enable simultaneous analysis of the neuronal and hemodynamic components of brain activity and do not interfere with each other (Chen et al., 2017; Luhmann et al.,2017). Hybrid systems, especially low-density hybrid systems, could be effective for attention recognition under study conditions. They are also practical, especially in naturalistic conditions. In a previous study, I implemented a hybrid system to study intellectual disability children during cognitive training (Zennifa et al., 2015; Iramina et al., 2010). In previous studies (Zennifa 2018, Zennifa 2019), I sought to implement a low-density hybrid system for attention level detection during cognitive tasks. The difference between those publications and this thesis is data labeling. In a previous publication, I combined features blink rates and pupillometry, but in this thesis, I just used pupillometry for data labeling. Correlation is a statistical term which in common usage refers to how close two variables are to having a linear relationship with each other as also mentioned by (Hall et al, 1999). Features with high correlation are more linearly dependent and hence have almost the same effect on the dependent variable. Table 17 shown the selected features based on merit using CFS method.

Table 17. Selected features

9(90 %) 2 mobilityfz
2(20 %) 7 betamaxfz
5(50 %) 8 betadensityfz
9(90 %) 15 relativethetafz
1(10 %) 19 mobilitypz
3(30 %) 20 complexitypz
5(50 %) 23 alphadensitypz
3(30 %) 25 betadensitypz
6(60 %) 35 complexityecg
10(100 %) 37 activityecg
8(80 %) 39 highfrequency
1(10 %) 40 heartrate
10(100 %) 44 activitytot1
4(40 %) 46 mobilitydeoxy1
2(20 %) 50 activityoxy1
4(40 %) 51 complexitytot2
8(80 %) 52 mobilitytot2
4(40 %) 57 complexityoxy2
1(10 %) 58 mobilityoxy2
6(60 %) 59 activityoxy2

The other issue I tried to solve was the generalizability of features across participants. (Li et al., 2018) offered a way to find EEG features in cross-participant emotion by exploring 18 kinds of linear and nonlinear EEG features. They examined the effectiveness of these 18 features from a dataset of emotional analysis, using physiological signals and a Shanghai Jiao Tong University (SJTU) emotion EEG dataset. Their results showed that the considered Hjorth parameter was suitable for analyzing EEG signals. In their evaluation, they found the Hjorth parameter in the beta rhythm led to the best mean recognition accuracy in cross-subject emotion recognition. In our study, we used nine types of linear and nonlinear features to find the most common feature to be used in attention recognition. As shown in **Table 17**, some Hjorth parameter was selected as a feature by CFS + kNN. (Oh et al., 2014) applied the Hjorth parameter for extracting EEG features. They found that the Hjorth parameter increased their EEG classification by 4.4%, on average. Following that, I suggest that the Hjorth parameter could be a useful feature for EEG-ECG- NIRS in attention recognition. After doing feature extraction I calculated predictive modeling by using several classifiers. kNN with k=1 was selected in this system after we compared it with other kernels and another classifier. Accuracy performance is higher in k=1 could be happened because the data is binary data, I also investigated other classifier performance for example SVM (55.88± 13.14%) (poly kernel), but the accuracy performance that I got is lower kNN (80.84± 3.88%). kNN classifier also mentioned in the study (Ahn et al., 2010) has the highest accuracy among another classifier especially when combine with CFS feature selector. In their study, they got the result of the kNN classifier. KNN has better accuracy than SVM, it's also mentioned in (Palaniappan et al, 2014) which this result also has been shown in my study.

3.6. Conclusions

This study sought to investigate the usability of a low-density hybrid system in attention recognition. My result showed the accuracy system of low-density EEG-ECG-NIRS (83.33± 5.95%) has the highest accuracy compare with EEG (81.90± 4.69%), ECG (82.51±3.57%), NIRS (78.37±7.12%). CFS+kNN algorithm also showed highest performance compare with other methods such as CFS+SVM (55.49± 27.89%), kNN (80.84± 3.88%) and SVM (55.88± 13.14%).

Chapter 4. General Discussion

I have proposed a parameter settings for data labeling in attention level detection and applied this labeling method to low-density EEG-ECG-NIRS. Several studies have proposed labeling methods such as self-assessment, observation, objective performance for detecting attention level. The system proposed in this thesis is specific parameter settings as the new labeling method for attention recognition using eye information and apply it in EEG-ECG-NIRS low density. Several research in multimodal systems required many channels (Ahn et al., 2017; Punsawad et al., 2017; Huang et al., 2018). But this thesis tried to use multimodal systems in few channels.

In chapter 2, I talked about the difference evaluation between self-assessment and the effect of attention level toward blink rates and pupillometry. Self-assessment has been compared for checking the similarity of this self-assessments method compared other methods such as observation and objective performance. Later on, self-assessment used as validation data in parameter setting using pupillometry to evaluate the difference evaluation. I found that error rates and difference evaluation of those systems comparing self-assessment is less than 21%. From chapter 2, I concluded that data from self-assessment can be the basis for developing our quantitative algorithm for new labeling method in attention level detection. Further analysis, I found that blink rates during high attention are lower than low attention in my cognitive task experiment. Pupillometry during high attention is bigger than low attention.

Generally, between each blink is an interval of 2–10 seconds; actual rates vary by individual averaging around 10 blinks per minute in a laboratory setting. However, when the eyes are focused on an object for an extended period, such as when reading, the rate of blinking decreases to about 3 to 4 times per minute (Bentivoglio et al., 2004). They measured the normal blink rate variations with behavioral tasks in 150 healthy volunteers, they found that blink rates during conversation are higher than resting and higher than reading. Blink rates higher in resting rather than reading was also reported by Paprocki et al., 2017. In their conclusion, they mentioned that eye blinks are connected to the higher cognitive process, so blink rates could be used as a marker of dopa- and gabaminergic functioning. This is also explained why our data shown tendency of blink rates in high attention is lower than low attention but there is no significant difference between both conditions. Probably I need to make the longer trial times to get the difference between high attention and low attention to become significantly different.

I also talked about the step to get the best threshold for attention level detection. Dewan et al., 2019 on their review article about engagement detection in online learning, mentioned that self-reporting (self-assessment) provides some useful information regarding learner engagement. This method depends on several factors are outside of the control of the researcher, such as learner's honesty, willingness to report their emotion and the accuracy of learners' perception about what they felt. Another method such as observational also has some limitations such as the observation metric that may not always be related to engagement but tend to measure compliance and willingness to adhere to rules rather than engagement. Which this statement they quoted from Whitehill et al., 2014. They mentioned very short response times on easy questions indicates that the learners are not engaged and are simply giving random answers without effort. On the other hand, my research proposed a new solution for this detection. Dewan et al., 2019, also mentioned method by using physiological data such as eye movement, neurological data tend to not interrupt learners in the engagement detection process. Because we did not find a significant difference in blink rates, so I decided to apply the last 4 second encoding time from pupillometry. The last 4-second pupillometry shown the optimum algorithm against other parameter settings.

In chapter 3, I applied my parameter settings to EEG-ECG-NIRS system. Applying pupillometry to neurophysiology and hemodynamic activity has been done because there is connection between pupillometry and brain activities. During a state of high attention, neurons in the locus coereleus fire rapidly, supplying high levels of noradrenaline to numerous targets throughout the body, inclusing both the eyes and brain. In the eye, this neurotransmitter mediates pupil dilation; in brain it regulates attention through its modulatory effects on brain activity (Gilzenrt et al., 2010; Donner and; Eldar et al., 2013). The combination of these three different approaches is commonly termed as a hybrid system. The integration of NIRS and EEG is complementary because they enable simultaneous analysis of the neuronal and hemodynamic components of brain activity and do not interfere with each other (Chen et al., 2017; Luhmann et al.,2017). Hybrid systems, especially low-density hybrid systems, could be effective for attention recognition under study conditions. They are also practical, especially in naturalistic conditions. Before choosing the algorithm for my model, I did several experiments to find the most suitable classifier in supervised machine learning. I considered using CFS + kNN for attention level evaluation after CFS + KNN showed the highest accuracy compared with other selector combinations. (Palaniappan et al., 2014) *compared* the performance of SVM and kNN for diagnosing respiratory pathologies.

Their result also showed that kNN has better accuracy than SVM. Although the combination of a CFS and kNN algorithm has been used by (Hu et al., 2018) for EEG attention recognition, their study used two types of search methods (i.e., best first search and greedy stepwise search). In my study, I applied this algorithm to a low-density hybrid system for attention level evaluation during cognitive tasks and used one searching algorithm. In this chapter, I applied my study to 24 participants. But due to the research condition, not noisy data that we only could analyze 10 participants. For example, a participant which has eyes fixation accuracy more than 1 degree will be excluded from our study. Data on which eye tracker set in 30 Hz will be excluded in our study. In our study, we used portable NIRS. This portable NIRS used LED light. To stick the portable NIRS to the subject prefrontal cortex, I use plastic stickers. When participants were sweating, this situation makes NIRS could not be glued on their prefrontal area completely it is also caused the NIRS light is scattered. One participant also got sick before doing our experiments but insisted to join. The other participants did not follow my instructions, for example, drank coffee within 2 hours before the experiment or did not put their head on chin rest when the task appears. Detail of our participant can be seen in **Appendix 4.**

This study has several limitations that leave some more questions for future work. Firstly about the Hjorth parameter which becomes the most selected feature to be used in attention level detection. In this thesis, we still not investigate in detail how the activities of the Hjorth parameter toward attention levels. I also have not studied in detail the features that we used toward brain activities, hemodynamic activities and autonomic activities. Due to the small participant pool, sampling could be a limitation of this study. Even though the small number of participants used for training may limit my conclusions, the preliminary results demonstrated the capability of our labeling method and the classification in low-density of hybrid EEG, ECG, and NIRS system for use in attention level detection. Correlation between EEG-ECG-NIRS toward pupillometry also becomes the limitation of this study. I did not investigate those physical activities correlation. But several studies already discussed the correlation between pupillometry and EEG-ECG-NIRS. (Dippel et al., 2017) investigated the correlation between theta band with pupillometry. They mentioned there is strong connectivity between neuronal activity and pupil diameter. Based on findings and theoretical models suggesting that the pupil diameter can be interpreted as a proximate of neurophenaprine system activity the results may be interpreted that the NE system modulates inhibitory control processes via theta band activity when the likelihood to inhibit a prepotent response tendency is low. (Mathot, 2018) also did a review about pupillometry and its psychology, physiology, and function. He mentioned that the pupil is controlled by 2 muscles that are innervated by the parasympathetic of the nervous system and caused the pupil to constrict. Pupil dilated innervated by the sympathetic nervous system. Pupillometry and P3 usage in task engagement also were investigated by Murphy et al 2011. In their research, they mentioned that both pupillometry and P3 were sensitive to the locus coeruleus-noradrenergic system. Pupillometry towards autonomic systems has been investigated (Wang et al., 2018). In the research which uses pupillometry, heart rate and skin conductance in emotional face task, they found that there are positive correlations between pupil diameter and high rate. They suggested that pupil size can be used as an index for arousal level regulated by the autonomic nervous system. Recently, (Numata et al., 2019) analyzed EEG, NIRS and pupil diameter toward attention during a free recall task. They found that there are significant physiological responses among those 3 modals. They recommend considering the characteristic of these multimodal in the development of applications requiring attention.

Overall, these results demonstrated that the proposed method can be used to be data labeling for other physiological signals such as electroencephalograph (EEG), electrocardiograph (ECG), and near-infrared spectroscopy (NIRS). After that, this parameter settings was applied to EEG-ECG-NIRS for attention level detection. Two-electrode wireless EEG, a wireless ECG, and two wireless channels NIRS has been used to detect attention levels during cognitive tasks. Algorithm CFS+kNN also shown highest performance compare with other methods such as CFS+SVM (55.49± 27.89%), kNN (80.84± 3.88%) and SVM (55.88± 13.14%). On the same time, I found that my result showed the accuracy system of EEG-ECG-NIRS (83.33± 5.95%) has the highest accuracy compare with EEG (81.90± 4.69%), ECG (82.51±3.57%), NIRS (78.37±7.12%).

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"if you think you will fail, you will be really failed. No one will trust you except yourself. If you doubt yourself who will trust you". This is my mantra when I would like to give up on anything.

I came to Japan in autumn 2013, after I finished my study in undergraduate with theme artificial intelligence to detect cardiovascular disease. My master study, entitled the change of EEG, ECG, and NIRS in Mental retardation child during four education training give me a new insight into brain sciences and developmental disorder. The next years after I completed my master thesis, I am thinking to develop a system by using hybrid systems. I was aspiring to be the youngest doctor from Indonesia in systems life sciences. But quarter life crisis was hit me and unfortunately, I should extend my studies. That moment was the bitterest experience in my life. But thanks to everyone who tries to convince me that life is not about age, but contribution. Finally, I finished my study in 2020, where Corona virus become a big terror in human existence.

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Appendix 1. Consent to participate example for experiment chapter 2.

九州大学

Consent to Participate in a Research Study

Kyushu University ● Neuroinformatic and Neuroimaging

Title of Study: **Engagement recognition**

Researcher:

Name: **Fadilla Zennifa** **Phone:** 090-9405-9378

Introduction

Engagement is a "meta construct" that encompasses "behavioral" (participation, positive conduct, effort), "emotional" (interest, positive emotions), and "cognitive" (psychological involvement in learning, self-regulation) dimensions. We are currently implementing hybrid technology system that can be used for monitoring engagement level during affective learning. In this experiment we attach Electrooculogram (EOG) and Eye tracking to record the eye movement of participants. We also recorded participant activities by using web camera and asking participant engagement states based on self-assessment. We are trying to do classification between high engagement level, neutral engagement level and low engagement level.

Purpose of Study

1. The present study explored the feasibility of monitoring hybrid indices of engagement.
2. Classify the engagement in 2 levels. (High, low)
3. Proof physiological activity in engagement recognition is the best parameter comparing other method (e.g self-assessment, behavior, observation)
4.

Description of the Study Procedures

- If you agree to be in this study, you will be asked to do the following things:
  1. Put the 3 electrodes on your Head
  2. Recording your behavior by using camera
  3. Tracking your gaze by using Eye tracking
  4. Doing visual stimulation activities

Risks/Discomforts of Being in this Study

- There are no reasonable foreseeable (or expected) risks.

Confidentiality

- The records of this study will be kept strictly confidential. Research records will be kept in a locked file, and all electronic information will be coded and secured using a password protected file. We will not include any information in any report we may publish that would make it possible to identify you.

Right to Refuse or Withdraw

- The decision to participate in this study is entirely up to you. You may refuse to take part in the study *at any time* without affecting your relationship with the researchers of this study or Kyushu University. Your decision will not result in any loss or benefits to which you are otherwise entitled. You have the right not to answer any single question, as well as to withdraw completely from the interview at any point during the process; additionally, you have the right to request that the interviewer not use any of your interview material.

Right to Ask Questions and Report Concerns

- You have the right to ask questions about this research study and to have those questions answered by me before, during or after the research. If you have any further questions about the study, at any time feel free to contact me, Fadilla Zennifa at 3sl14005p@s.kyushu-u.ac.jp or by telephone at 090-9405-9378. If you like, a summary of the results of the study will be sent to you.
- If you have any problems or concerns that occur as a result of your participation, you can report them to Kyushu University.

Consent

- Your signature below indicates that you have decided to volunteer as a research participant for this study, and that you have read and understood the information provided above. You will be given a signed and dated copy of this form to keep, along with any other printed materials deemed necessary by the study researchers.

Subject's Name: ______________________________

Subject's Signature: ______________________________ Date: ____________________

Researcher's Signature: ______________________________ Date: ____________________

Appendix 2. Consent to participate example for experiment chapter 3.

九州大学

Consent to Participate in a Research Study

Kyushu University ● Neuroinformatic and Neuroimaging

Title of Study: **<u>Engagement detection by using Integrated Wearable Technology</u>**

Researcher:

Name: **Fadilla Zennifa** **Phone:** 090-9405-9378

Introduction

Engagement is a "meta construct" that encompasses "behavioral" (participation, positive conduct, effort), "emotional" (interest, positive emotions), and "cognitive" (psychological involvement in learning, self-regulation) dimensions. We are currently implementing hybrid technology system that can be used for monitoring engagement level during affective learning. The hybrid system is consisted by wireless electroencephalography (EEG). Near Infrared spectroscopy (NIRS), and Electrocardiography (ECG). In this experiment we also attach Electrooculogram (EOG) and Eye tracking to record the eye movement of participants. We are trying to do classification between high engagement level, neutral engagement level and low engagement level.

Purpose of Study

5. The present study explored the feasibility of monitoring hybrid indices of engagement.
6. Classify the engagement in 3 levels. (High, neutral, low)
7. Proof hybrid systems is better than standalone systems in term engagement detection.
8. Get better performance of classification rate

Description of the Study Procedures

- If you agree to be in this study, you will be asked to do the following things:
    5. Put the 8 electrodes on your Head and Body
    6. Recording your behavior by using camera
    7. Tracking your gaze by using Eye tracking
    8. Doing visual stimulation activities

Risks/Discomforts of Being in this Study

- There are no reasonable foreseeable (or expected) risks.

Confidentiality

- The records of this study will be kept strictly confidential. Research records will be kept in a locked file, and all electronic information will be coded and secured using a password protected file. We will not include any information in any report we may publish that would make it possible to identify you.

Right to Refuse or Withdraw

- The decision to participate in this study is entirely up to you. You may refuse to take part in the study *at any time* without affecting your relationship with the researchers of this study or Kyushu University. Your decision will not result in any loss or benefits to which you are otherwise entitled. You have the right not to answer any single question, as well as to withdraw completely from the interview at any point during the process; additionally, you have the right to request that the interviewer not use any of your interview material.

Right to Ask Questions and Report Concerns

- You have the right to ask questions about this research study and to have those questions answered by me before, during or after the research. If you have any further questions about the study, at any time feel free to contact me, Fadilla Zennifa at 3sl14005p@s.kyushu-u.ac.jp or by telephone at 090-9405-9378. If you like, a summary of the results of the study will be sent to you.
- If you have any problems or concerns that occur as a result of your participation, you can report them to Kyushu University.

Consent

- Your signature below indicates that you have decided to volunteer as a research participant for this study, and that you have read and understood the information provided above. You will be given a signed and dated copy of this form to keep, along with any other printed materials deemed necessary by the study researchers.

Subject's Name: ______________________________

Subject's Signature: ______________________________ Date: ____________________

Researcher's Signature: ______________________________ Date: ____________________

Appendix 3. Experiment report summary for chapter 2.

1. S1, (24 years)

   Calibration less than 1 degree. 60 Hz

   Experiment: 11: 30

   Right handed

2. S2 (25 years)

   Calibration less than 1 degree 60 Hz

   Experiment: 10: 52

   Right handed

3. S3 (25 years)

   Calibration less than 1 degree 60 Hz

   Experiment: 13:42

   Right handed

4. S4 (22 years)

   Calibration less than 1 degree 60 hz

   Both handed

   Morning session

5. S5 (29 years)

   Calibration less than 1 degree 60 Hz

   Right handed

Afternoon session

6. S6 (22)

   Left handed

   Calibration less than 1 degree 60 Hz

   Morning session

7. S7 (27)

   Calibration less than 1 degree 60 Hz

   Right handed

   Afternoon session

8. S8 (25)

   Calibration less than 1 degree 60 Hz

   Right handed

   Morning session

9. S9 (26)

   Calibration less than 1 degree 60 Hz

   Right handed

   Afternoon session

10. S10 (22)

    Calibration less than 1 degree 30 Hz

    Right handed

    Morning session

11. S11 (24)

    Calibration less than 1 degree 60 Hz

    Right handed

    Morning session

12. S12 (24)

    Calibration less than 1 degree 60 Hz

    Right handed

    Morning session

13. S13 (21)

    Calibration less than 1 degree 60 Hz

    Right handed

    Morning session

14. S14 (21)

    Calibration less than 1 degree 60 Hz

    Right handed

    Morning session

15. S15 (21)

    Calibration less than 1 degree 60 Hz

    Right handed

    Morning session

16. S16 (22)

    Calibration less than 1 degree 60 Hz

    Right handed

    Morning session

17. S17 (23)

    Calibration less than 1 degree 60 Hz

    Left handed

    Morning session

18. S18 (23)

    Calibration less than 1 degree 60 Hz

    Right handed

    Morning session

Appendix 4. Experiment report summary for chapter 3.

1. **S1 : 8/7/2018 (23) (training data) (Japan)**

   Eye tracking frequency sampling: 60 Hz.

   We did not analyze when the subject put the answer.

   Only when the question appear (10 second).

   Flow of S1: **Arithmetic-FDS-BDS**

   Monitor illumination: 72

   Font size: 30

   Right handed

2. **S2: 9/7/2018 (27) (Indonesia)**

   Eye tracking frequency sampling 60 Hz

   Monitor illumination 72 something

   Experiment supposed to be worked well but the NIRS signals cannot be recorded.

   Flow of S2: **FDS-BDS-Arithmetic**

   Font size: 30

   Right handed

3. **S3 : 10/ July 2018 (28) (India)**

Accuracy for eye tracking is 1.4 we cannot finish the experiment, experiment only conduct till BDS.

Monitor illumination: 50

Her experiment flow: **FDS-BDS-Arithmetic**

Font size: 30

Right handed

4. **S4: 11/ July 2018 (25) <u>(Japan)</u>**

Accuracy for eye tracking <0.5 we did 4 times calibration in several blocks.

Monitor Illumination 50.

Flow of S4: **FDS- Arithmetic-BDS**

Right Handed

Calibration

1. Start experiment (resting)
2. Start experiment (without resting)
3. Ar 3 (without resting)
4. BDS 3 (without resting)

5. S5: 13 July 2018 (25) <u>(Thailand)</u>

Accuracy eye tracking:

1. First calibration 0.61 degree *including resting
2. Second calibration 0.64 degree *without resting
3. BDS 2, Third calibration 0.23 degree *without resting
4. AR 1,Fourth calibration degree *without resting

Eye tracking frequency sampling : 30 Hz

Right Handed

Flow : **BDS - FDS – Arithmetic**

6. **S6 : 15 July 2018 (28) <u>(Indonesian)</u>**

Calibration only once. Accuracy 0.17

Eye tracking frequency sampling: 30 Hz

Right Handed

Flow: Arithmetic -BDS–FDS

7. S7: 16 July 2018 (24) <u>(Indonesian)</u>

Calibration only once. Accuracy 0.31 degree

Eye tracking frequency sampling: 60 Hz

Right Handed

Flow: BDS-Arithmetic-FDS.

8. **S8 : 17 July 2018 (23)(Japan)**

Calibration only once. Accuracy 0.16 degree

Eye tracking frequency sampling: 60 Hz

Sometimes we could not catch the NIRS signal (only one channel). The nirs signal cannot be cacthed.

FDS 1.1 **->** NIRS only can detect from 1 channel.

Ar 2.1 **->** NIRS only can detect from 1 channel.

Right Handed

Flow: FDS-BDS-Arithmetic

9. **S9 (24)**

Accuracy: 0.21 degree.

Eye tracking fs= 30 Hz

Flow: FDS-BDS-Arithmetic

Right handed

10. **S10**(August 1st,2018. Japanese) (23)

Flow : FDS-BDS-Arithmetic

Left handed

Eye tracking fs = 60 Hz

Using glasses

In the end cannot use eye tracking because the glasses reflected.

11. **S11**(2nd august, 2018 Indonesia) (27) **(subject got sick)**

Flow: arithmetic**-** bds-fds (ok)

12. **S12** (DATA IS BAD) (21)

Eye tracker and NIRS can’t be detected

13. **S13** 5 AUGUST 2018 (27)

    ARITHMETIC-BDS-FDS

    EYE TRACKING FS = 60 Hz

14. **S14,** (27) Myanmar

    FDS-BDS-Arithmeric

    Not using eyetracking

    Not following instruction

15. **S15** (22)

    Left handed

    Eye tracking FS= 60 Hz

    Flow :

    Arithmetic-BDS-FDS (ok)

16. **S16 (24)**

    BDS-Arithmetic-FDS

    Right handed

    FS= 60 Hz (ok)

17. **S17 (25)** (Indonesian, training data)

    BDS-Arithmetic-FDS

    Fs =60 hz (ok)

18. **S18** (Thai, 21)

    Ar-bds-fds

    Fs= 60 Hz (ok)

19. **S19**

BDS- Arithmetic FDS (21)

Right handed

Without eye tracking

20. **S20**(22 years old, Vietnames)

    Arithmetic-BDS-FDS

    Fs = 60 Hz

    Right handed

    Accuracy below 1.

21. **S21** (23 years old, Chinese)

    BDS-Ar-FDS

    FS= 30 Hz

    Right handed

    Accuracy 1.36

22. **S22** (21 years Old, Vietnames)

    BDS-AR- FDS

    FS= 60 Hz

    Both Right handed and left handed. (Ambidextrous)

    Accuracy 0.3

23. **S23** (23 years old, Chinese)

    BDS-FDS-AR

    FS= 60 Hz

    Right handed

    Accuracy 0.1

24. **S24** (28 years old, Indonesian)

BDS-FDS-AR

FS= 60 Hz

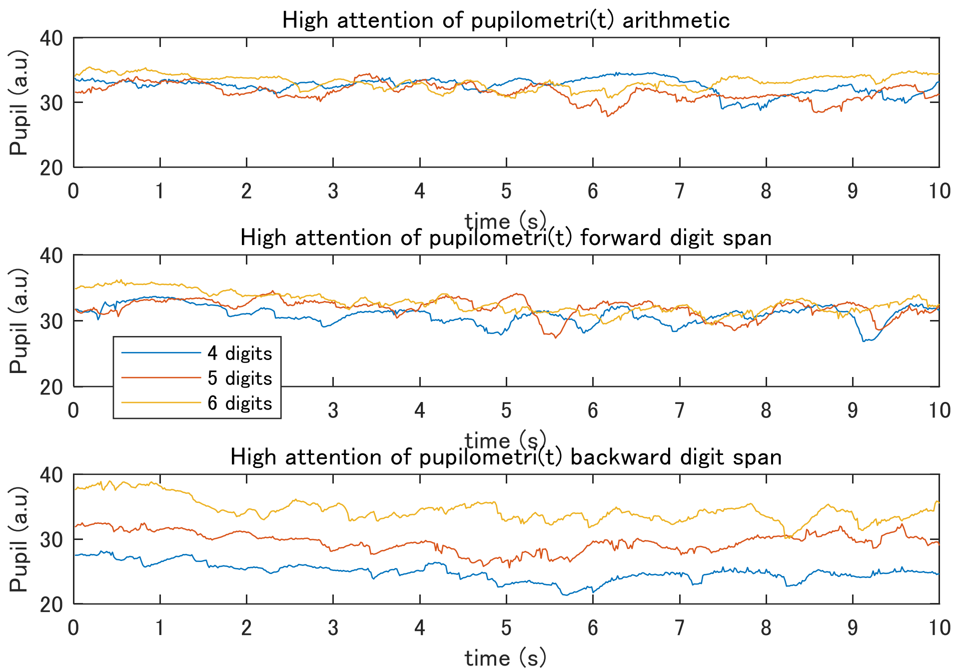
Right handed

Accuracy 0.9

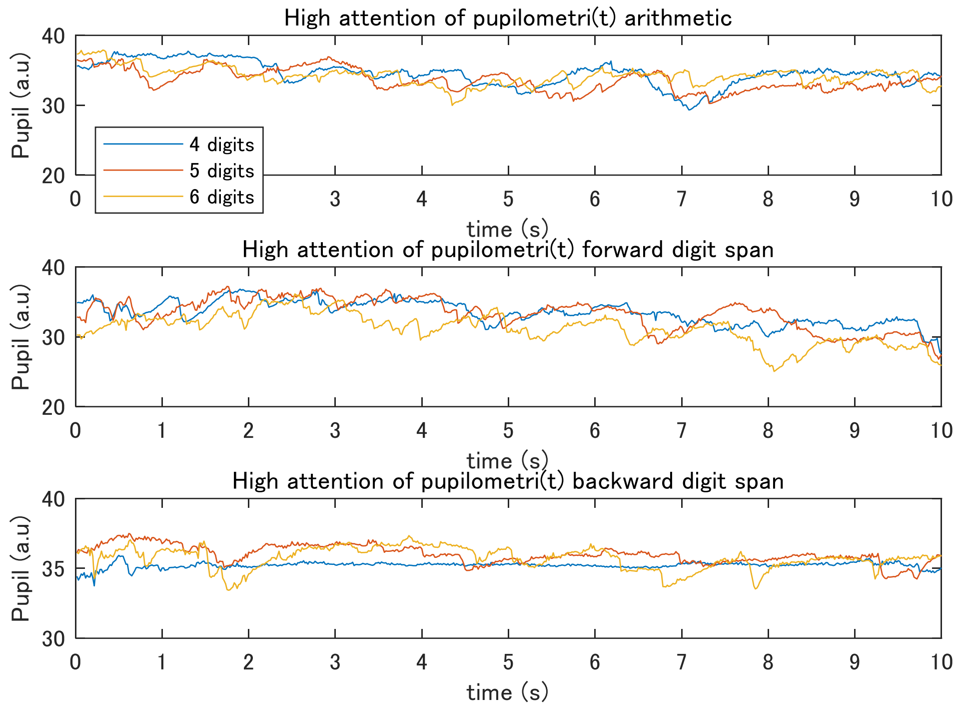
Appendix 5. pupillometry activities based on tasks

one subject is excluded due to no value in states.

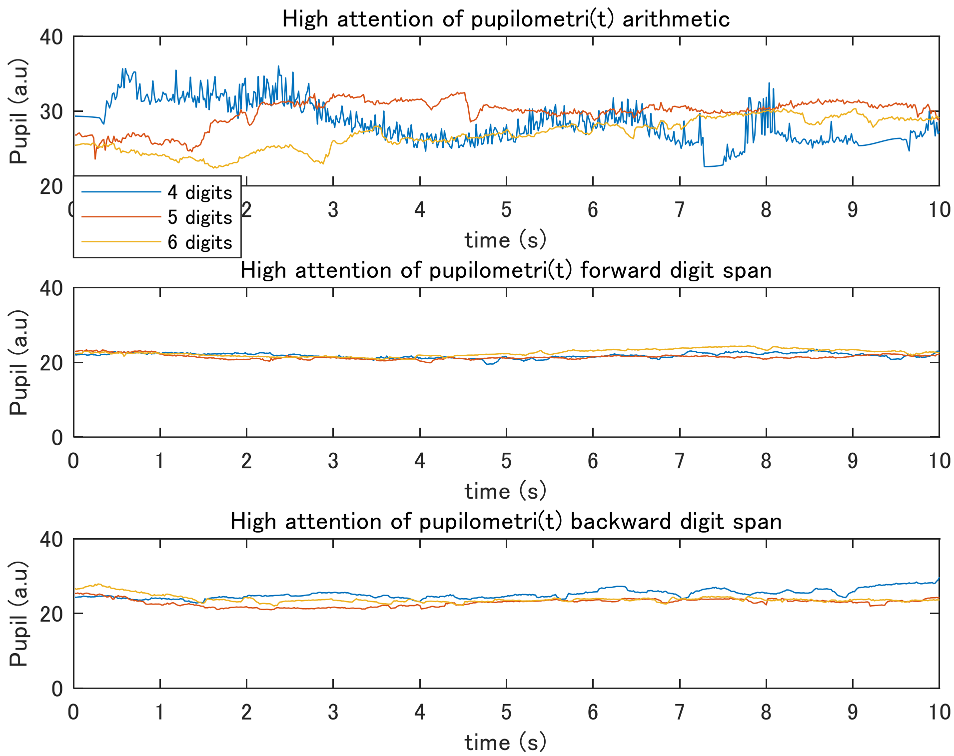
S1



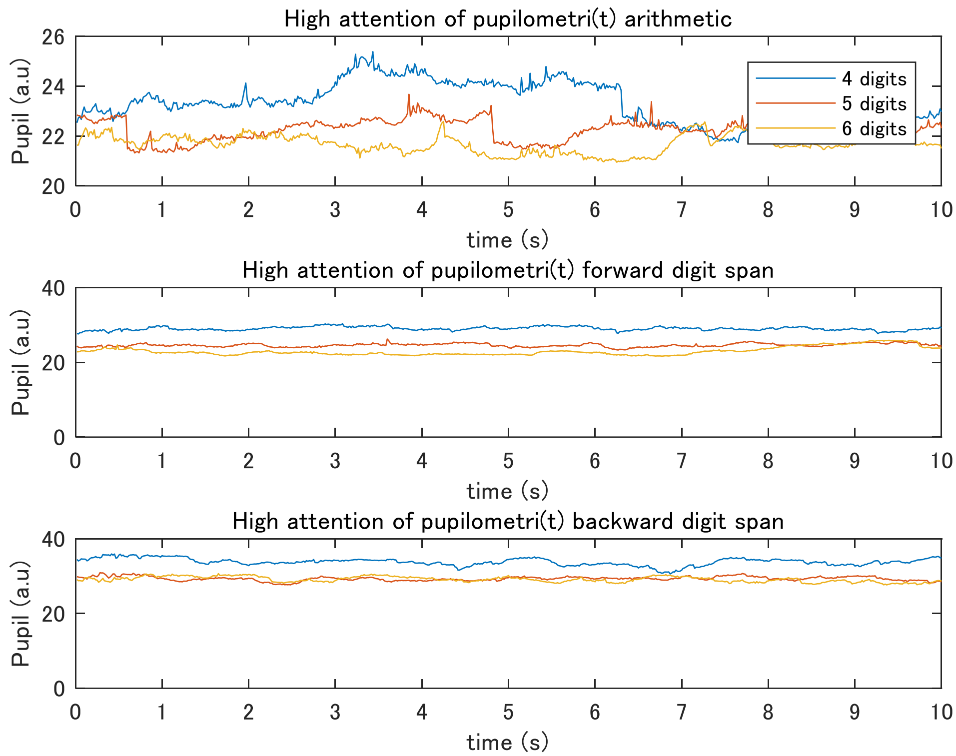
S2


High attention of pupilometri(t) arithmetic
Pupil (a.u)
time (s)
4 digits
5 digits
6 digits
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

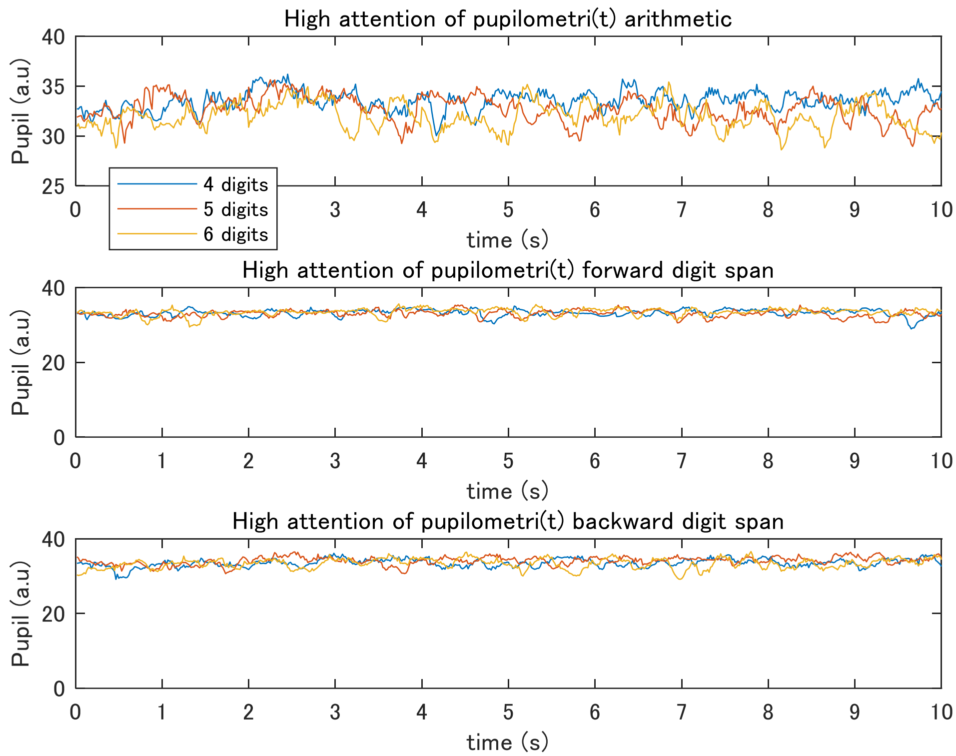
S3


High attention of pupilometri(t) arithmetic
Pupil (a.u)
time (s)
4 digits
5 digits
6 digits
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

S4

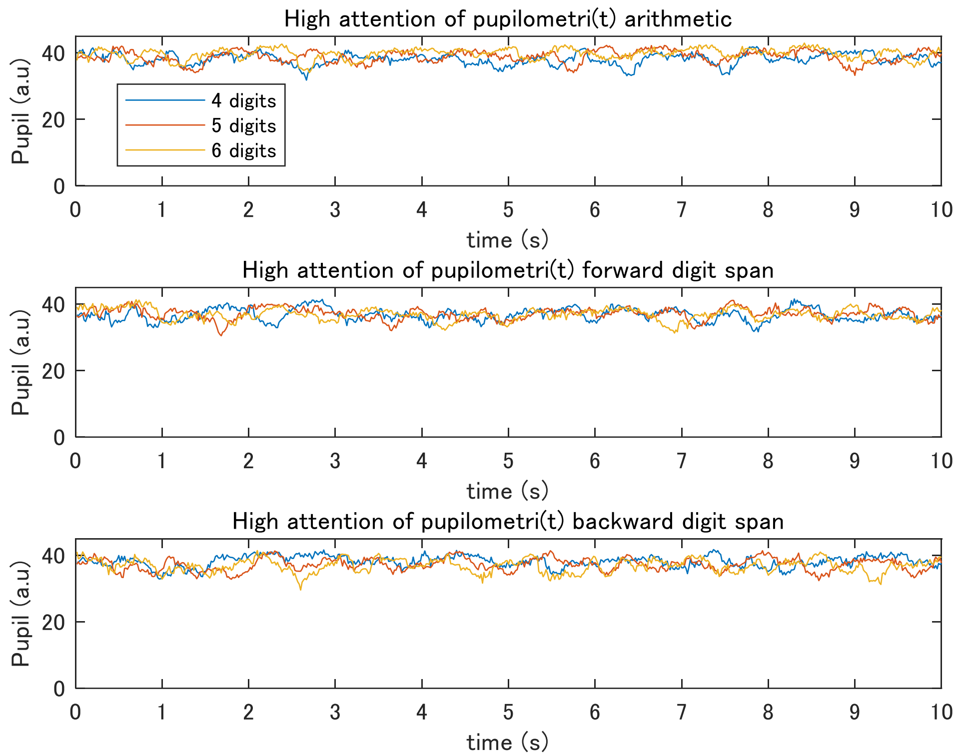

High attention of pupilometri(t) arithmetic
Pupil (a.u)
time (s)
4 digits
5 digits
6 digits
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

S5

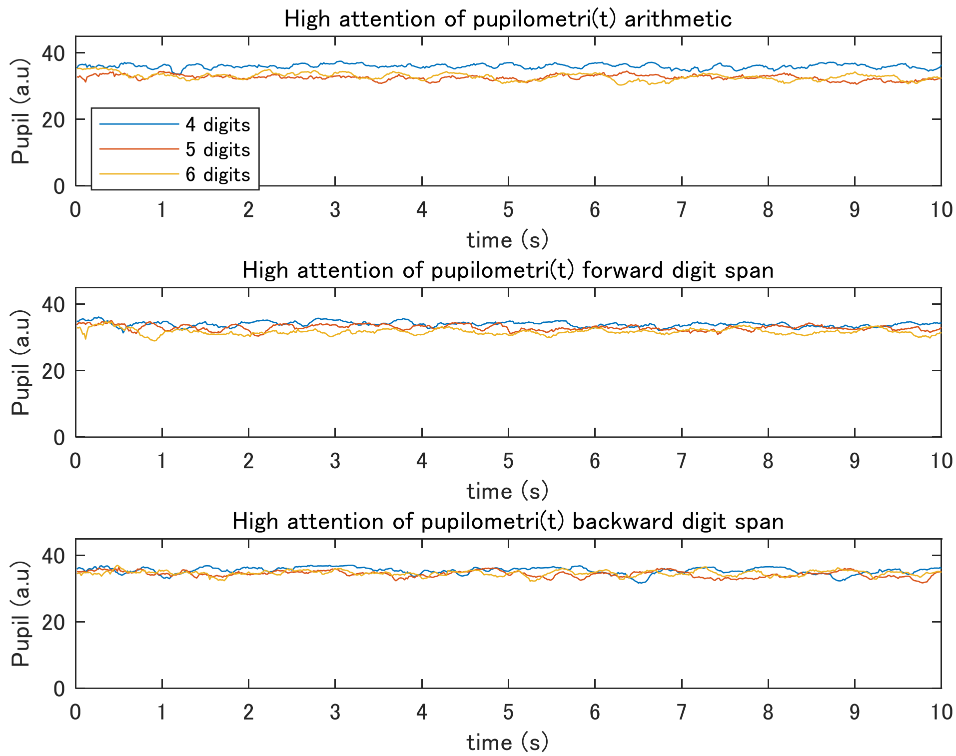


High attention of pupilometri(t) arithmetic
Pupil (a.u)
4 digits
5 digits
6 digits
time (s)
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

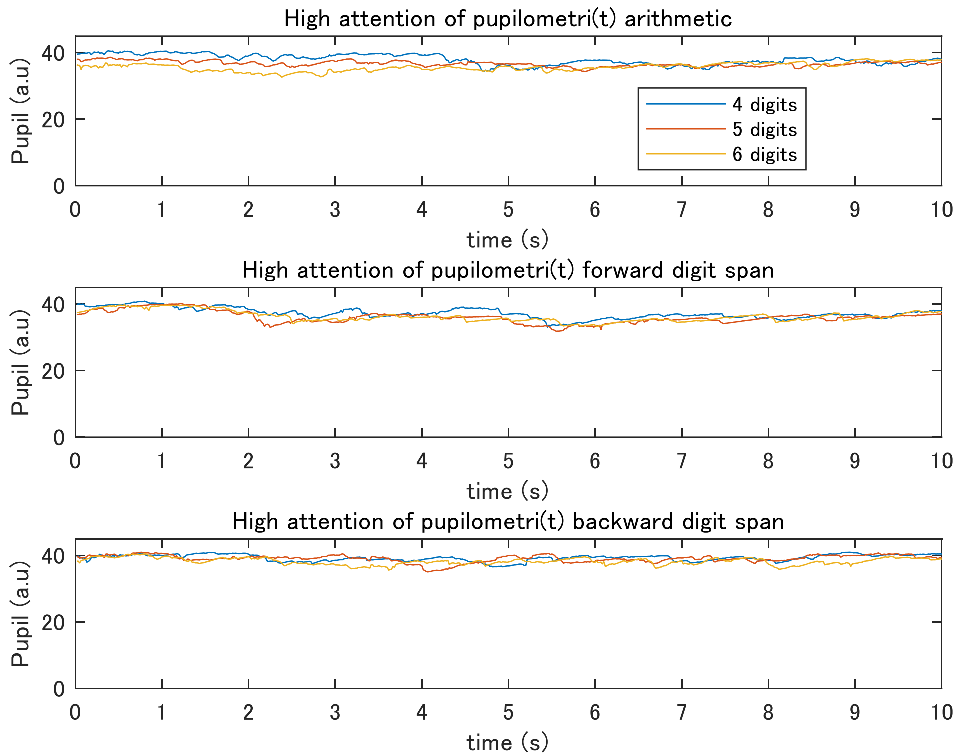
S6


High attention of pupilometri(t) arithmetic
Pupil (a.u)
4 digits
5 digits
6 digits
time (s)
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

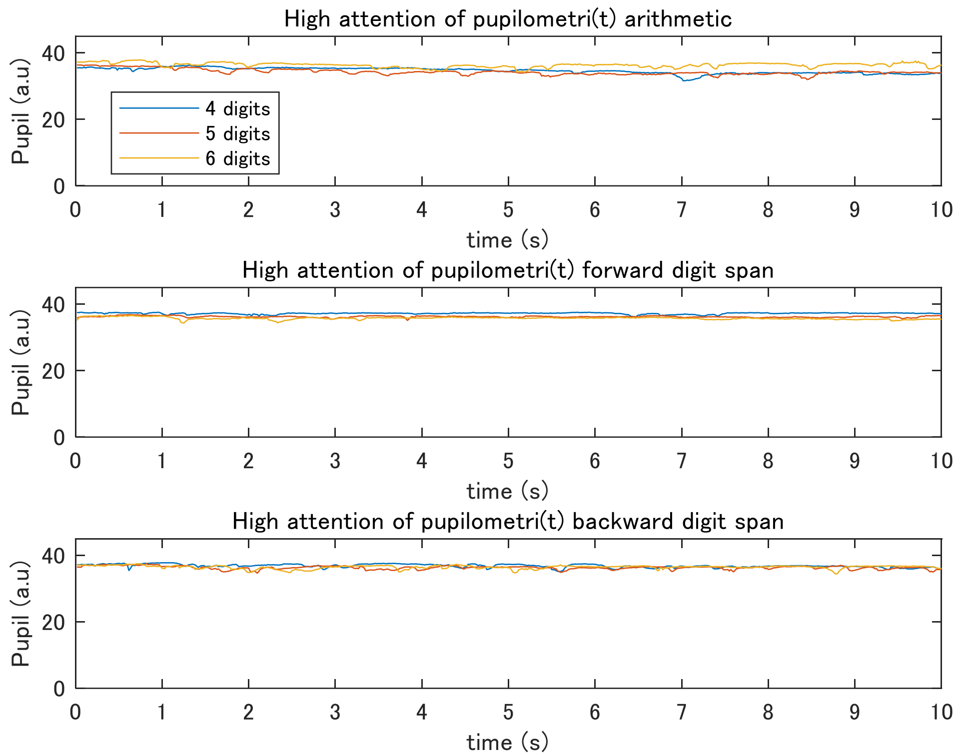
S7


High attention of pupilometri(t) arithmetic
Pupil (a.u)
40
20
0
4 digits
5 digits
6 digits
0
1
2
3
4
5
6
7
8
9
10
time (s)
High attention of pupilometri(t) forward digit span
Pupil (a.u)
40
20
0
0
1
2
3
4
5
6
7
8
9
10
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
40
20
0
0
1
2
3
4
5
6
7
8
9
10
time (s)

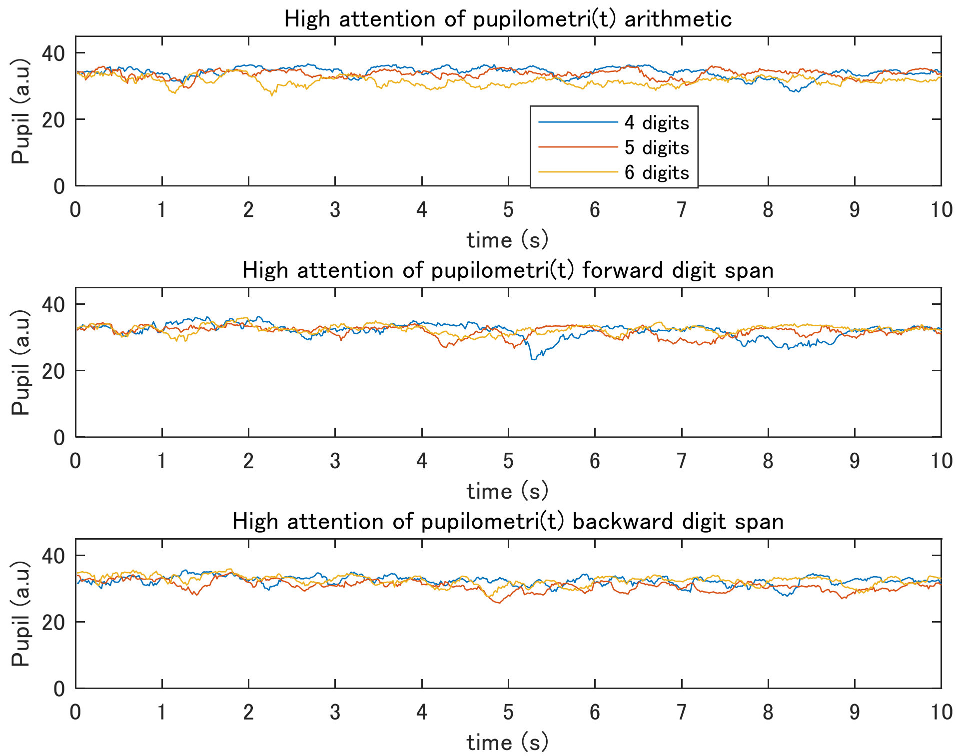
S8


High attention of pupilometri(t) arithmetic
Pupil (a.u)
time (s)
4 digits
5 digits
6 digits
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

<u>S9</u>

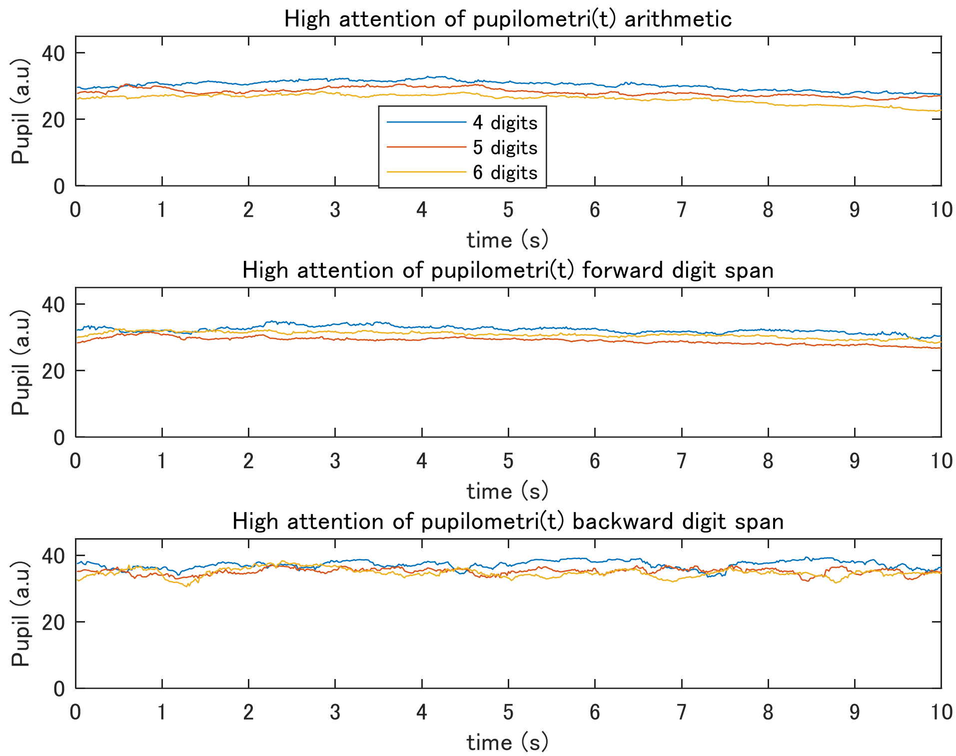

High attention of pupilometri(t) arithmetic
Pupil (a.u)
4 digits
5 digits
6 digits
time (s)
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

S 10



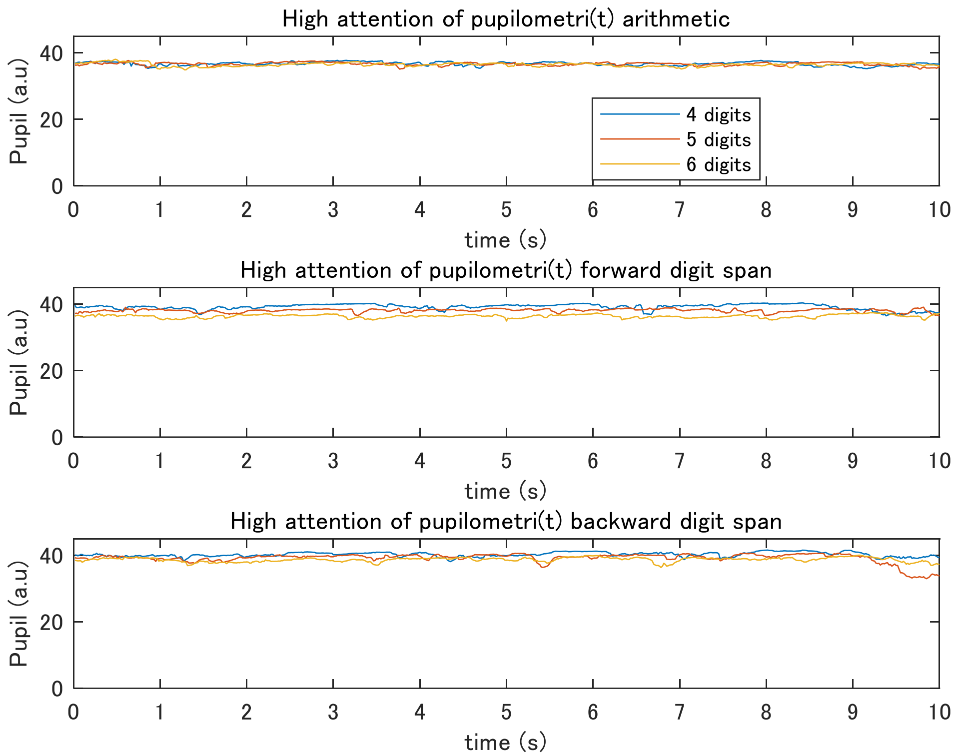
High attention of pupilometri(t) arithmetic
Pupil (a.u)
40
20
0
4 digits
5 digits
6 digits
0 1 2 3 4 5 6 7 8 9 10
time (s)
High attention of pupilometri(t) forward digit span
Pupil (a.u)
40
20
0
0 1 2 3 4 5 6 7 8 9 10
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
40
20
0
0 1 2 3 4 5 6 7 8 9 10
time (s)

S11

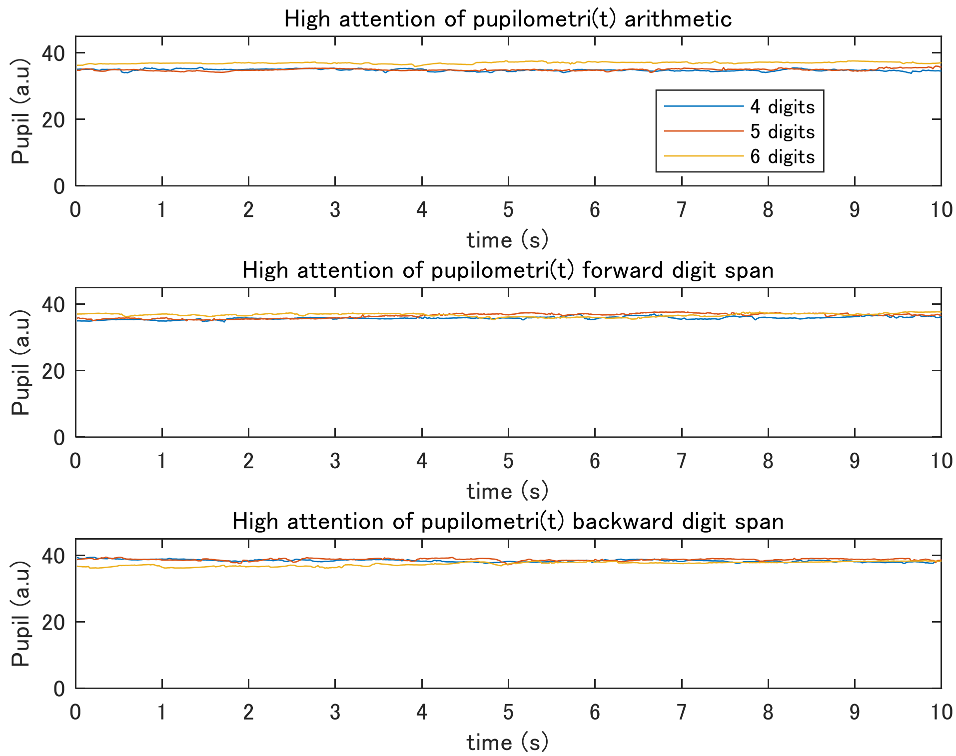


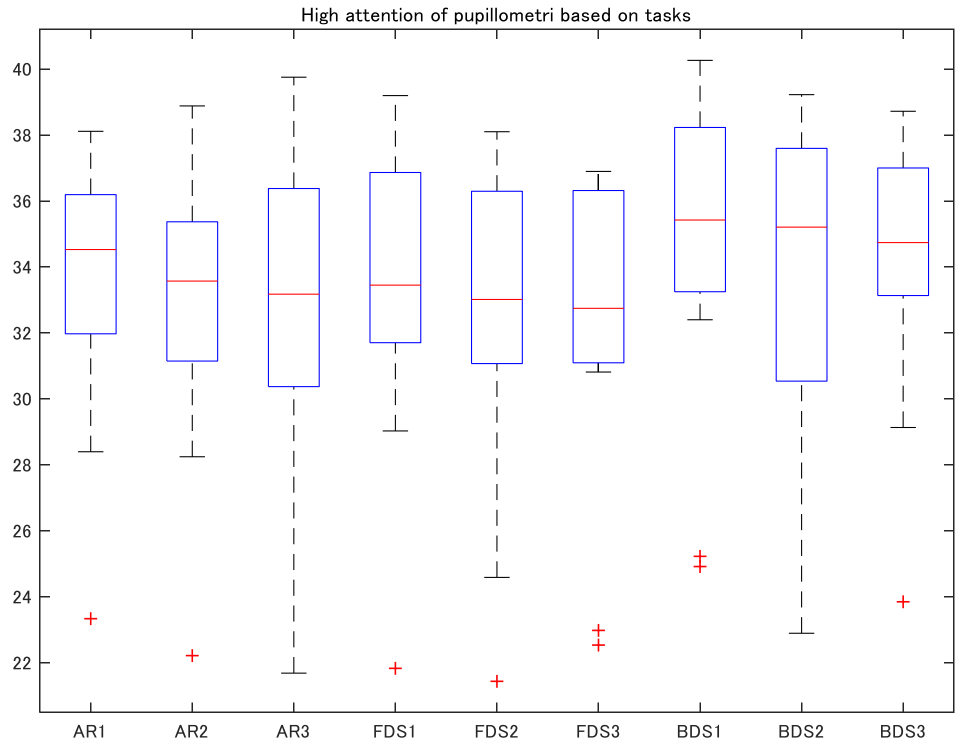
High attention of pupilometri(t) arithmetic
Pupil (a.u)
4 digits
5 digits
6 digits
time (s)
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

S12


High attention of pupilometri(t) arithmetic
Pupil (a.u)
time (s)
4 digits
5 digits
6 digits
High attention of pupilometri(t) forward digit span
Pupil (a.u)
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
time (s)

S 13


High attention of pupilometri(t) arithmetic
Pupil (a.u)
40
20
0
0
1
2
3
4
5
6
7
8
9
10
time (s)
4 digits
5 digits
6 digits
High attention of pupilometri(t) forward digit span
Pupil (a.u)
40
20
0
0
1
2
3
4
5
6
7
8
9
10
time (s)
High attention of pupilometri(t) backward digit span
Pupil (a.u)
40
20
0
0
1
2
3
4
5
6
7
8
9
10
time (s)


High attention of pupillometri based on tasks
40
38
36
34
32
30
28
26
24
22
AR1
AR2
AR3
FDS1
FDS2
FDS3
BDS1
BDS2
BDS3

Appendix 6. Script program in this thesis.

Blink rates detection

```
for T = 1 : event(P);      %////////////T=タスク??////////////

  for N = 1 : 2
     if(N==1);EOG_data=teog1(:,T);end
         if(N==2); EOG_data=teog2(:,T);end

%baseline drift removal
[p,s,mu] = polyfit((1:numel(EOG_data))',EOG_data,6);
f_y = polyval(p,(1:numel(EOG_data))',[],mu);

EOG_data = EOG_data - f_y;        % Detrend data

    if(N == 1)
channel1=EOG_data;
 end

 if(N == 2)
channel2=EOG_data;
 end
    end
    Vv(:,T)= channel1-channel2;
    peakblink = findpeaks(Vv,'MinPeakHeight',200);
numOccurances(P,T)=length(peakblink);
    meanblink=mean(numOccurances);
    zblinkscore(P,T)=((numOccurances(P,T))-meanblink)/std(numOccurances);
  end
 end
```

Interpolation pupillometi

```
function X = naninterp(X)
% Interpolate over NaNs
X(isnan(X)) = interp1(find(~isnan(X)), X(~isnan(X)), find(isnan(X)),'cubic');
return
```

```
psize = eyetracking(:,9);       %time
psize(psize <= 20) = NaN;
psize=naninterp(psize); %interpolation
fs = 60;    %sampling 60 hz %reducing the data lost
```

```
%cc = 0;
m = 60;     %1minute?a?I?f?[?^?d俳?I??
Count = 0;

%psize is located in channel 9

%20120820
plus=0;
min = [2    2   3   3   4   4   5   5   5   6   6   7   7   7   8   8   9   9   10  10
10  13  13  13  14  14  15  15  16  16  17  17  17  18  18  19  19  20  20  20  21  23
23  24  24  25  25  26  26  27  27  28  28  28  29  29  30  30  31  31  32  34  34  35
35  35  36  36  37  37  37  38  38  39  39  39  40  40  41  41  41  43  44  44  45  45
45  46  46  47  47  47  48  48  48  49  49  50  50  50  51  53  53  54  54  54  55  55
56  56  56  57  57  58  58  58  59  59  60  60  60  62  62  63  63  64  64  64  65  65
66  66  66  67  67  68  68  68  69  69  70  72  72  72  73  73  74  74  74  75  75  75
76  76  77  77  77  78  78  79  79  81  81  82  82  82  83  83  84  84  84  85  85  86
86  86  87  87  87  88];
sec = [32   44  11  41  8   36  3   27  52  18  43  9   34  59  24  50  15  42  6   31
57  6   32  58  24  53  22  49  15  41  5   30  54  19  46  10  38  2   33  58  25  19
45  16  46  12  43  9   38  5   31  1   28  56  22  48  14  43  9   37  3   9   38  3
27  50  22  46  12  35  58  22  46  10  34  58  21  45  9   33  58  52  15  40  4   32
59  23  45  11  35  59  23  47  60  24  47  11  34  57  20  17  40  4   29  52  18  44
10  34  58  23  46  10  34  58  23  46  11  35  58  36  59  24  47  11  35  58  20  43
8   30  54  17  42  7   31  54  17  42  6   5   29  51  15  39  2   24  47  10  34  56
20  45  9   32  57  20  43  7   30  23  45  8   31  54  18  41  5   28  52  16  39  4
27  51  14  37  60  23];

event = [1]

for t=180;

    for T= 1 : event(t);     %///////////T = task number////////////

    range(T,1) = fs*(m*min(t)+Count+sec(t));
        Count = Count + 10;
    range(T,2) = fs*(m*min(t)+Count+sec(t))-1;

    tpupil(:,T) = psize(range(T,1):range(T,2));

    end
```

Z score pupillometri

```
    if(N == 1);
        Data_Ana(:,T) = tpupil(:,T);end
        bobo(P,T)=mean(Data_Ana(:,T));
        bobo1 = mean(bobo);
        %meanpups=mean (pupil);
        zblinkscore=(bobo-bobo1)/std(bobo);
```

Plotting based on task

```
figure()
subplot(3,1,1)
plot (haar1)
hold on
plot (haar2)
hold on
plot (haar3)
title('High attention of pupilometri(t) arithmetic')
xlabel('time (s)')
xticks([0 60 120 180 240 300 360 420 480 540 600])
xticklabels({'0','1','2','3','4','5','6','7','8','9','10' })
ylabel('Pupil (a.u)')
legend('4 digits','5 digits','6 digits')
%xlim([0 2])
ylim([0 45])



subplot(3,1,2)
plot (hafr1)
hold on
plot (hafr2)
hold on
plot (hafr3)
title('High attention of pupilometri(t) forward digit span')
xlabel('time (s)')
xticks([0 60 120 180 240 300 360 420 480 540 600])
xticklabels({'0','1','2','3','4','5','6','7','8','9','10' })
ylabel('Pupil (a.u)')
%xlim([0 2])
ylim([0 45])
```

```
subplot(3,1,3)
plot (habr1)
hold on
plot (habr2)
hold on
plot (habr3)
title('High attention of pupilometri(t) backward digit span')
xlabel('time (s)')
xticks([0 60 120 180 240 300 360 420 480 540 600])
xticklabels({'0','1','2','3','4','5','6','7','8','9','10' })
ylabel('Pupil (a.u)')
%xlim([0 2])
ylim([0 45])
```

EEG

```
for T = 1 : event(P);

    if(N == 1);Data_Ana = tfz(:,T);end
    if(N == 2);Data_Ana = tpz(:,T);end

      cuttoff=[0.5 65];
          x=Data_Ana;

                L = length(x(:));  % Length of signal
                waveletFunction = 'db8'; %because frequency sampling is 500 Hz
                [C,L] = wavedec(x,7,waveletFunction);
                % Calculation The Coificients Vectors
                cD1 = detcoef(C,L,1);                  %NOISY
                cD2 = detcoef(C,L,2);                  %NOISY
                cD3 = detcoef(C,L,3);                  %NOISY
                cD4 = detcoef(C,L,4);                  %GAMMA
                cD5 = detcoef(C,L,5);                  %BETA
                cD6 = detcoef(C,L,6);                  %ALPHA
                cD7 = detcoef(C,L,7);                  %THETA
                cA7 = appcoef(C,L,waveletFunction,7);  %DELTA
                %%%% Calculation the Details Vectors
                D1 = wrcoef('d',C,L,waveletFunction,1); %NOISY
                D2 = wrcoef('d',C,L,waveletFunction,2); %NOISY
                D3 = wrcoef('d',C,L,waveletFunction,3); %NOISY
                D4 = wrcoef('d',C,L,waveletFunction,4); %GAMMA
                D5 = wrcoef('d',C,L,waveletFunction,5); %BETA
```

```
                D6 = wrcoef('d',C,L,waveletFunction,6); %ALPHA
                D7 = wrcoef('d',C,L,waveletFunction,7); %THETA
                A7 = wrcoef('a',C,L,waveletFunction,7); %DELTA


                POWER_DELTA = ((A7.^2))/length(A7);
                POWER_THETA = ((D7.^2))/length(D7);
                POWER_ALPHA = ((D6.^2))/length(D6);
                POWER_BETA =  ((D5.^2))/length(D5);
                POWER_GAMMA = ((D4.^2))/length(D4);

        pTheta(:,T)  = POWER_THETA;
        pAlpha(:,T)  = POWER_ALPHA;
        pBeta(:,T)   = POWER_BETA;
        pGamma(:,T)   = POWER_GAMMA;

%maximum power
Thetamax(P,T)=max(pTheta(:,T));
Alphamax(P,T)=max(pAlpha(:,T));
Betamax(P,T)=max(pBeta(:,T));
Gammamax(P,T)=max(pGamma(:,T));

%center frequency(:,T)



        %sumpower (power density integral)
        tTheta(P,T) = sum(pTheta(:,T));  %theta パ??[値の?代v
        tAlpha(P,T) = sum(pAlpha(:,T));  %alpha パ??[値の?代v
        tBeta(P,T) = sum(pBeta(:,T));
        tGamma(P,T) = sum(pGamma(:,T));

 %relative power
        rT(P,T)=tTheta(P,T)/(tTheta(P,T)+tAlpha(P,T)+tBeta(P,T)+tGamma(P,T)); %theta
baris 1, study baris 2
        rA(P,T)=tAlpha(P,T)/(tTheta(P,T)+tAlpha(P,T)+tBeta(P,T)+tGamma(P,T)); %alpha
        rB1(P,T)=tBeta(P,T)/(tTheta(P,T)+tAlpha(P,T)+tBeta(P,T)+tGamma(P,T)); %beta
        rG(P,T)=tGamma(P,T)/(tTheta(P,T)+tAlpha(P,T)+tBeta(P,T)+tGamma(P,T));
 %maximum



%Hjorthparameter

%activity
boleh (:,T)= x;
```

```
activity(P,T) = var(boleh(:,T));

dxV = diff(x);
dxV(:,T)= dxV;
ddxV(:,T)= diff (dxV(:,T));

vardxV(P,T)= var(dxV(:,T));

%Mobility
Mobility (P,T)= sqrt(vardxV(P,T) /activity(P,T));

difmobil = diff (Mobility);

%complexity
%complexity(P,T) =difmobil(:,T)/Mobility(:,T);

mx2(P,T) = mean((boleh(:,T)).^2);

mdx2(P,T) = mean((dxV(:,T)).^2);

mddx2(P,T) = mean((ddxV(:,T)).^2);

mob(P,T) = mdx2(P,T) / mx2(P,T);
complexity(P,T) = sqrt(mddx2(P,T) / mdx2(P,T) - mob(P,T));

%spectral entropy
 %calculate power spectral entropy
    poweraja = pwelch (x);
    poweraja1 (:,T)= poweraja;
    es(P,T)= entropy (poweraja1(:,T));

%singular value decomposition
svddecomposition = svd(x);
svddecomposition(:,T)= svddecomposition;
svdaja (P,T)=svddecomposition(:,T);
  eSVD(P,T) = entropy (svddecomposition (:,T));

 %kolmogorov complexcity
otak (:,T)= x;
kolmo(P,T) = kolmogorov(otak(:,T));



 %lyapunov
```

```
end


    end
  if(N == 1);
      r1T =  rT; r1A = rA; r1B1 = rB1;r1G=rG;%relative power
      mobility1=Mobility; complexity1=complexity;activity1=activity; %Hjorth Parameter

Thetamax1=Thetamax;Alphamax1=Alphamax;Betamax1=Betamax;Gammamax1=Gammamax; %maxpower
      tTheta1=tTheta;tGamma1=tGamma;tAlpha1=tAlpha;tBeta1=tBeta; %power density
integral
      es1=es; %spectral entropy
      kolmo1=kolmo;
      %chanel 1
        end
  if(N == 2);
      r2T = rT;r2A = rA; r2B1 = rB1; r2G=rG;
      mobility2=Mobility; complexity2=complexity;activity2=activity;
      Thetamax2=Thetamax;Alphamax2=Alphamax;Betamax2=Betamax;Gammamax2=Gammamax;
      tTheta2=tTheta;tGamma2=tGamma;tAlpha2=tAlpha;tBeta2=tBeta;
     es2=es;
     kolmo2=kolmo;
      %chanel 2
        end

end

save('resulteeg','r1T','r1A','r1B1','r1G','mobility1','complexity1','activity1','Theta
max1','Alphamax1','Betamax1','Gammamax1','tTheta1','tGamma1','tAlpha1','tBeta1','es1',
'kolmo1','r2T','r2A','r2B1','r2G','mobility2','complexity2','activity2','Thetamax2','A
lphamax2','Betamax2','Gammamax2','tTheta2','tGamma2','tAlpha2','tBeta2','es2','kolmo2'
)
```

ECG

```
for T = 1 : event(P);     %////////////T=タスク??///////////

    %*************************************filtering*************************************
********************
        Data_Ana = tecg(:,T);
         filteroder = 3;
    ECG_data=Data_Ana;
    %**************x**********************findpeaks**********************************
*********************
```

```
    t = 1:length(ECG_data);
        %pks = ピ?[クの?U?
        %locs_Rwave = ピ?[クの時の時間

        [pks,locs_Rwave] =
findpeaks(ECG_data,'MinPeakHeight',0.5,'MinPeakDistance',200); %di sini saya ganti
jadi 500
        ECG_inverted = -tecg(:,T);
        [~,locs_Swave] =
findpeaks(ECG_inverted,'MinPeakHeight',0.5,'MinPeakDistance',200);
        smoothECG = sgolayfilt(ECG_data,7,21);
        [~,min_locs] = findpeaks(-smoothECG,'MinPeakDistance',40);
        % Peaks between -0.2mV and -0.5mV
        locs_Qwave = min_locs(smoothECG(min_locs)>-0.5 & smoothECG(min_locs)<-0.2);

        %RRInterval = tecg(locs_Rwave,N);
        %x = RRInterval;

        % Determine the RR intervals
        %diff = 次のピ?[ク時間-?。のピ?[ク時間を繰り返すため?A要素?狽ｪ１?ｺなくなる
        RLocsInterval = diff(locs_Rwave);%RLocsInterval = 周期Tみたいなもん
        %figure(8);
        %plot(RLocsInterval);hold on

        %calculate the heart rate signal
        myheartrate (P,T) = 60 ./ (median(RLocsInterval) ./ 500); %karena frekuensi
sampling 500



        % Derive the HRV signal
        tHRV = locs_Rwave(2:end);
        HRV = 1./RLocsInterval;%HRV = 周波?杷みたいなもん %?S?変動?iHeart Rate
Variability/HRV?j

        % Plot the signals
        %figure;
        %a1 = subplot(2,1,1);
        %plot(t/fs,ECG_data/fs,'b',locs_Rwave/fs,pks/fs,'*r');grid on;
        %legend('ECG signal','R-wave');
        %a2 = subplot(2,1,2);
        %plot(tHRV/fs,HRV);grid on;
        %xlabel(a2,'Time(s)','FontSize', 15)
        %ylabel(a1,'ECG (mV)','FontSize', 15)
        %ylabel(a2,'HRV (Hz)','FontSize', 15)
```

```
        %************************************powerspectrum****************************
****************************
%PSD HRV
        xHRV = HRV;
       L = length(xHRV);  % Length of signal
        NFFT = 2^nextpow2(L);       % ?M??y)の長さの次のべき??
        dt = 1/fs;                   %1/1000
        t = (1:L)*dt-dt;             %まず時間軸を??ｬする
        f = t/dt/dt/L;           %周波?博ｲを??ｬする
        f = f(1:NFFT/2+1);          %計算した周波?博ｲ前半分のみを取り?oす
        Y = fft(xHRV)/(L/2);           %fft関?狽ﾉよる計算
        Y = Y(1:NFFT/2+1);         %fftdataの前半分のみを取り?oす

        pHRV = abs(Y).^2; %ﾊﾟ??[計算
        p_totHRV = sum(pHRV);

        %Low Frequency (LF), from 40 to 150 mHz,
        RLF= [0.04 0.15];
        [b2, a2] = butter(filteroder, RLF/(fs/2)); % Generate filter coefficients
        xlf = filter(b2, a2, HRV);
        L = length(xlf);  % Length of signal
        NFFT = 2^nextpow2(L);       % ?M??y)の長さの次のべき??
        dt = 1/fs;                   %1/1000
        t = (1:L)*dt-dt;             %まず時間軸を??ｬする
        f = t/dt/dt/L;           %周波?博ｲを??ｬする
        f = f(1:NFFT/2+1);          %計算した周波?博ｲ前半分のみを取り?oす
           Y = fft(xlf)/(L/2);           %fft関?狽ﾉよる計算
        Y = Y(1:NFFT/2+1);         %fftdataの前半分のみを取り?oす

        pLF = abs(Y).^2; %ﾊﾟ??[計算
        p_totLF = sum(pLF);
        p_meanLF =  mean(pLF);
        pr_LF(P,T) = p_totLF./p_totHRV;
        pmeanlf(P,T) = p_meanLF;

        %High Frequency (HF), from 150 to 400 mHz.
        RHF= [0.15 0.4];
        [b3, a3] = butter(filteroder, RHF/(fs/2)); % Generate filter coefficients
        xhf = filter(b3, a3, HRV);
        L = length(xhf);  % Length of signal
        NFFT = 2^nextpow2(L);       % ?M??y)の長さの次のべき??
        dt = 1/fs;                   %1/1000
        t = (1:L)*dt-dt;             %まず時間軸を??ｬする
        f = t/dt/dt/L;           %周波?博ｲを??ｬする
        f = f(1:NFFT/2+1);          %計算した周波?博ｲ前半分のみを取り?oす
           Y = fft(xhf)/(L/2);           %fft関?狽ﾉよる計算
```

```
        Y = Y(1:NFFT/2+1);          %fftdataの前半分のみを取り?oす

        pHF = abs(Y).^2; %パ??[計算
        p_totHF = sum(pHF);
        p_meanHF = mean(pHF);
        pr_HF(P,T) = p_totHF./p_totHRV;
        pmeanhf(P,T) = p_meanHF;

        %satuan vkuadrat/Hz-1
        LFHF(P,T) = pmeanlf(P,T)/pmeanhf(P,T);


 %spectral entropy
 %calculate power spectral entropy
    poweraja = pwelch (ECG_data);
    poweraja1 (:,T)= poweraja;
    es(P,T)= entropy (poweraja1(:,T));

 %Hjorthparameter

%activity
boleh (:,T)= ECG_data;
activity(P,T) = var(boleh(:,T));

dxV = diff(ECG_data);
dxV(:,T)= dxV;
ddxV(:,T)= diff (dxV(:,T));

vardxV(P,T)= var(dxV(:,T));

%Mobility
Mobility (P,T)= sqrt(vardxV(P,T) /activity(P,T));

difmobil = diff (Mobility);

%complexity
%complexity(P,T) =difmobil(:,T)/Mobility(:,T);

mx2(P,T) = mean((boleh(:,T)).^2);

mdx2(P,T) = mean((dxV(:,T)).^2);

mddx2(P,T) = mean((ddxV(:,T)).^2);
```

```
mob(P,T) = mdx2(P,T) / mx2(P,T);
complexity(P,T) = sqrt(mddx2(P,T) / mdx2(P,T) - mob(P,T));

%singular value decomposition
svddecomposition = svd(ECG_data);
svddecomposition(:,T)= svddecomposition;
svdaja (P,T)=svddecomposition(:,T);
  eSVD(P,T) = entropy (svdaja (P,T));

%kolmogorov entropy
jantung (:,T)= tecg;
kolmo(P,T) = kolmogorov(jantung(:,T));

    end

end

save('resultecg','complexity','Mobility','activity','es','pmeanhf','myheartrate','kolmo')
```

NIRS

```
Data_Ana = tc1oxy(20:122,T);

        %Hjorthparameter

        %activity
        activityoxy1(:,T) = var(Data_Ana);

        dxV = diff(Data_Ana);
        dxV(:,T)= dxV;
        ddxV(:,T)= diff (dxV(:,T));
        vardxV(:,T)= var(dxV(:,T));

        %Mobility
        Mobilityoxy1 (:,T)= sqrt(vardxV(:,T) ./activityoxy1(:,T));

        difmobil = diff (Mobilityoxy1);

        %complexity
        %complexity(P,T) =difmobil(:,T)/Mobility(:,T);

        mx2(:,T) = mean((Data_Ana).^2);
```

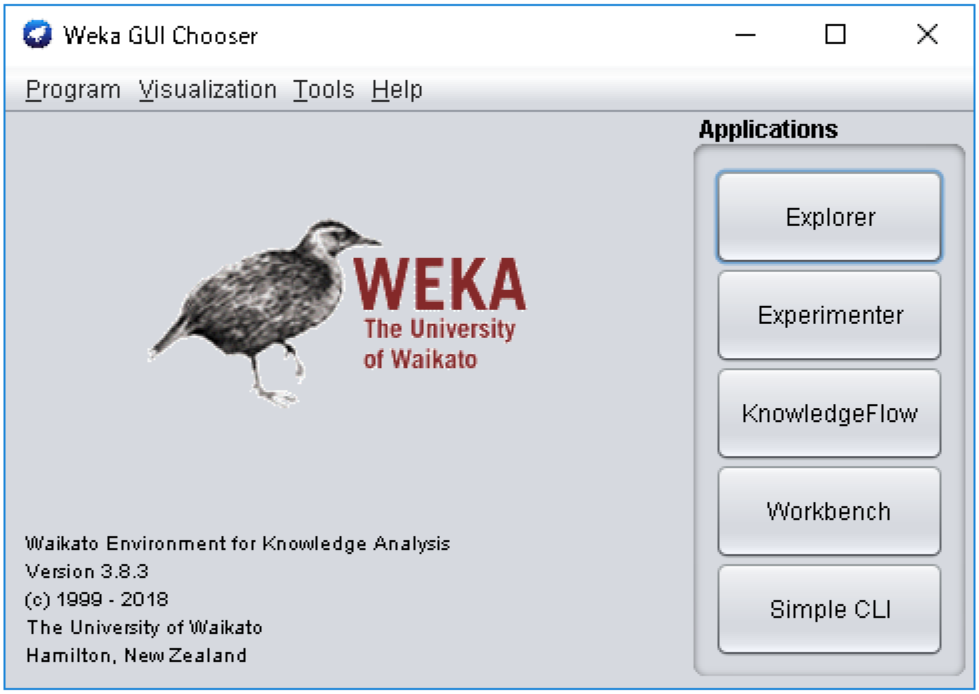
```
        mdx2(:,T) = mean((dxV(:,T)).^2);
        mddx2(:,T) = mean((ddxV(:,T)).^2);
        mob(:,T) = mdx2(:,T) ./ mx2(:,T);
        complexityoxy1(:,T) = sqrt(mddx2(:,T) ./ mdx2(:,T) - mob(:,T));



 end

%Deoxyhemoglobin ch 1
    for T = 1 : event(P);     %///////////T=タスク??///////////
        Data_Ana = tc1deoxy(20:122,T);

      %Hjorthparameter
      %activity
      activitydeoxy1(:,T) = var(Data_Ana);
      dxV = diff(Data_Ana);
      dxV(:,T)= dxV;
      ddxV(:,T)= diff (dxV(:,T));
      vardxV(:,T)= var(dxV(:,T));
      %Mobility
        Mobilitydeoxy1 (:,T)= sqrt(vardxV(:,T) ./activitydeoxy1(:,T));
        difmobil = diff (Mobilitydeoxy1);
        %complexity
        %complexity(P,T) =difmobil(:,T)/Mobility(:,T);
        mx2(:,T) = mean((Data_Ana).^2);
        mdx2(:,T) = mean((dxV(:,T)).^2);
        mddx2(:,T) = mean((ddxV(:,T)).^2);
        mob(:,T) = mdx2(:,T) ./ mx2(:,T);
        complexitydeoxy1(:,T) = sqrt(mddx2(:,T) ./ mdx2(:,T) - mob(:,T));
      end
%totalhemoglobin ch 1
     for T = 1 : event(P);     %///////////T=タスク??///////////
        Data_Ana = tc1total(20:122,T);

         %Hjorthparameter
        %activity
        activitytot1(:,T) = var(Data_Ana);
        dxV = diff(Data_Ana);
        dxV(:,T)= dxV;
        ddxV(:,T)= diff (dxV(:,T));
        vardxV(:,T)= var(dxV(:,T));
        %Mobility
        Mobilitytot1 (:,T)= sqrt(vardxV(:,T) ./activitytot1(:,T));
        difmobil = diff (Mobilitytot1);
        %complexity
        %complexity(P,T) =difmobil(:,T)/Mobility(:,T);
```

```
        mx2(:,T) = mean((Data_Ana).^2);
        mdx2(:,T) = mean((dxV(:,T)).^2);
        mddx2(:,T) = mean((ddxV(:,T)).^2);
        mob(:,T) = mdx2(:,T) ./ mx2(:,T);
        complexitytot1(:,T) = sqrt(mddx2(:,T) ./ mdx2(:,T) - mob(:,T));

    end
%oxyhemoglobin ch 2
    for T = 1 : event(P);      %////////////T=タスク??////////////
        Data_Ana = tc2oxy(20:122,T);
       %Hjorthparameter
        %activity
        activityoxy2(:,T) = var(Data_Ana);
        dxV = diff(Data_Ana);
        dxV(:,T)= dxV;
        ddxV(:,T)= diff (dxV(:,T));
        vardxV(:,T)= var(dxV(:,T));
        %Mobility
        Mobilityoxy2 (:,T)= sqrt(vardxV(:,T) ./activityoxy2(:,T));
        difmobil = diff (Mobilityoxy2);
        %complexity
        %complexity(P,T) =difmobil(:,T)/Mobility(:,T);
        mx2(:,T) = mean((Data_Ana).^2);
        mdx2(:,T) = mean((dxV(:,T)).^2);
        mddx2(:,T) = mean((ddxV(:,T)).^2);
        mob(:,T) = mdx2(:,T) ./ mx2(:,T);
        complexityoxy2(:,T) = sqrt(mddx2(:,T) ./ mdx2(:,T) - mob(:,T));

    end
%deoxyhemoglobin ch 2
    for T = 1 : event(P);      %////////////T=タスク??////////////
        Data_Ana = tc2deoxy(20:122,T);

   %Hjorthparameter
        %activity
        activitydeoxy2(:,T) = var(Data_Ana);
        dxV = diff(Data_Ana);
        dxV(:,T)= dxV;
        ddxV(:,T)= diff (dxV(:,T));
        vardxV(:,T)= var(dxV(:,T));
        %Mobility
        Mobilitydeoxy2 (:,T)= sqrt(vardxV(:,T) ./activitydeoxy2(:,T));
        difmobil = diff (Mobilitydeoxy2);
        %complexity
        %complexity(:,T) =difmobil(:,T)/Mobility(:,T);
        mx2(:,T) = mean((Data_Ana).^2);
```

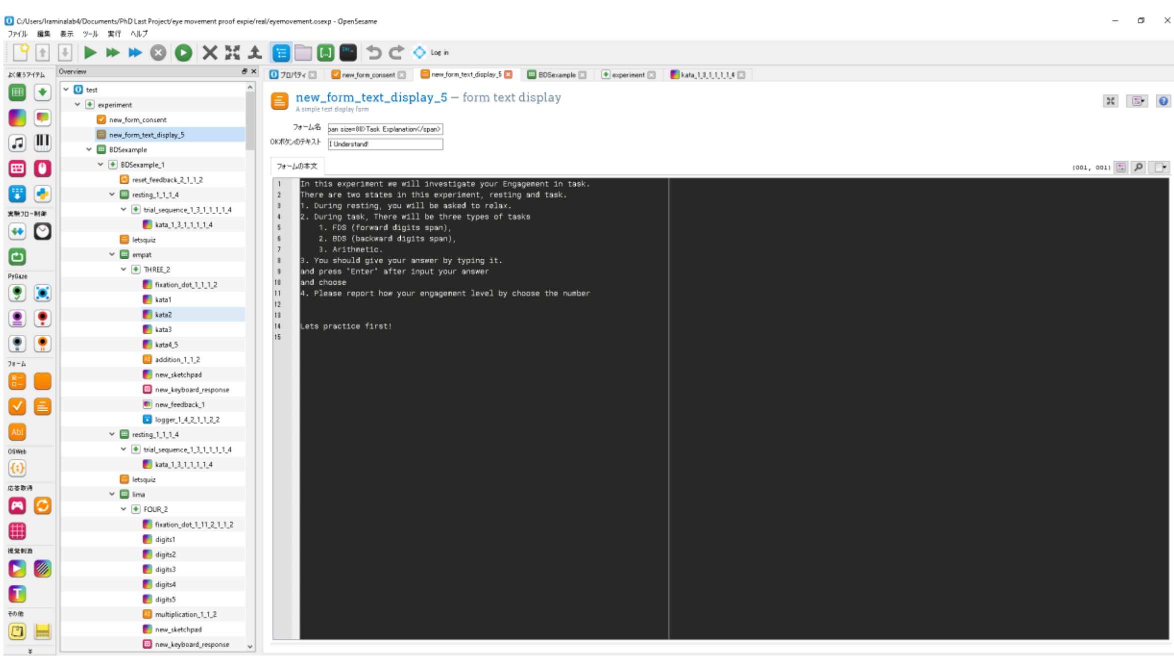
```
        mdx2(:,T) = mean((dxV(:,T)).^2);
        mddx2(:,T) = mean((ddxV(:,T)).^2);
        mob(:,T) = mdx2(:,T) ./ mx2(:,T);
        complexitydeoxy2(:,T) = sqrt(mddx2(:,T) ./ mdx2(:,T) - mob(:,T));


    end
%total hemoglobin ch 2
    for T = 1 : event(P);      %///////////T=タスク??///////////
        Data_Ana = tc2total(20:122,T);
        %Hjorth:arameter
        %activity
        activitytot2(:,T) = var(Data_Ana);
        dxV = diff(Data_Ana);
        dxV(:,T)= dxV;
        ddxV(:,T)= diff (dxV(:,T));
        vardxV(:,T)= var(dxV(:,T));
        %Mobility
        Mobilitytot2 (:,T)= sqrt(vardxV(:,T) ./activitytot2(:,T));
        difmobil = diff (Mobilitytot2);
        %com:lexity
        %com:lexity(:,T) =difmobil(:,T)/Mobility(:,T);
        mx2(:,T) = mean((Data_Ana).^2);
        mdx2(:,T) = mean((dxV(:,T)).^2);
        mddx2(:,T) = mean((ddxV(:,T)).^2);
        mob(:,T) = mdx2(:,T) ./ mx2(:,T);
        complexitytot2(:,T) = sqrt(mddx2(:,T) ./ mdx2(:,T) - mob(:,T));
    end
```

Appendix 7. Supporting software in this thesis

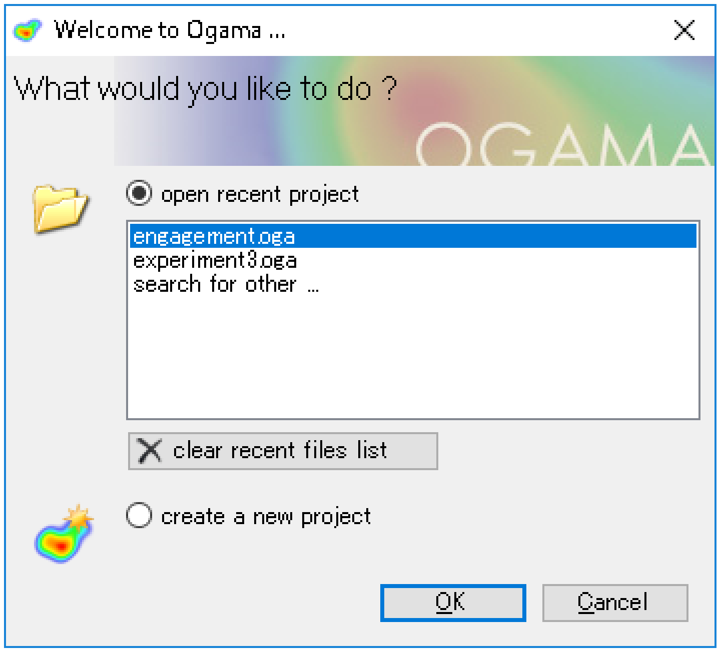
Weka (for classification/data mining)



Open sesame (for stimulation)



Ogama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experiment3.oga
search for other ...
clear recent files list
create a new project
OK
Cancel