

# Evaluation and estimation of discomfort during continuous work with Mixed Reality systems by deep learning

Yoshihiro Banchi<sup>1</sup>, Kento Tsuchiya<sup>2</sup>, Masato Hirose<sup>2</sup>, Ryu Takahashi<sup>2</sup>, Riku Yamashita<sup>2</sup>, Takashi Kawai<sup>2</sup>

<sup>1</sup>Waseda Research Institute for Science and Engineering ; Tokyo, Japan

<sup>2</sup>Department of Intermedia Art and Science, School of Fundamental Science and Engineering, Waseda University; Tokyo, Japan

## Abstract

Mixed reality systems are often reported to cause user discomfort. Therefore, it is important to estimate the timing at which discomfort occurs and to consider ways to reduce or avoid it. The purpose of this study is to estimate the discomfort of the user while using the MR system. Psychological and physiological indicators during the task were measured using the MR system, and a deep learning model was constructed to estimate psychological indicators from physiological indicators. As a result of 4-fold cross-validation, the average F1-value of each discomfort score was 0.608 for 1 (Nothing at all), 0.555 for 2 (Slightly Discomfort), and 0.290 for 3 (Very Discomfort). This result suggests that mild discomfort can be detected with a certain degree of accuracy.

## Introduction

Recently, the XR systems are accelerating development. Some of the XR devices are stand-alone or portable, and they can easily experience an XR environment. Of course, Mixed reality (MR) is one of the XR systems, and the stand-alone or portable types of MR devices are used for product design or entertainment.

MR systems are often reported to cause user discomfort. The most prevalent theory is sensory conflict as the mechanism of discomfort [1], but it has not yet been established a method for improving. Therefore, it is important to estimate the timing at

which discomfort occurs and to consider ways to reduce or avoid it.

## Purpose

The purpose of this study is to estimate the discomfort of the user while using the MR system. To achieve the purpose, clarify the correspondence between subjective and objective indicators, and estimate the discomfort level from objective indicators using deep learning.

## Method

### Task

The experimental task was a 3-D puzzle that could be played continuously. It is a combination of seven-colored and differently shaped blocks into a 3x3 cube. In this experiment, to control the observation and assembly operation, the assembly procedure was presented one by one, and the participants were asked to assemble the puzzle for 15 minutes according to the presentation procedure.

### Conditions

MR conditions and Monitor conditions were set as experimental conditions. Under MR conditions, the assembly procedure was presented through a prototype of the MREAL Display MD20 (Canon, video see-through type HMD). Under the Monitor conditions, the assembly procedure was presented to a 24-inch monitor (Dell U2412M). The puzzle assembly position was

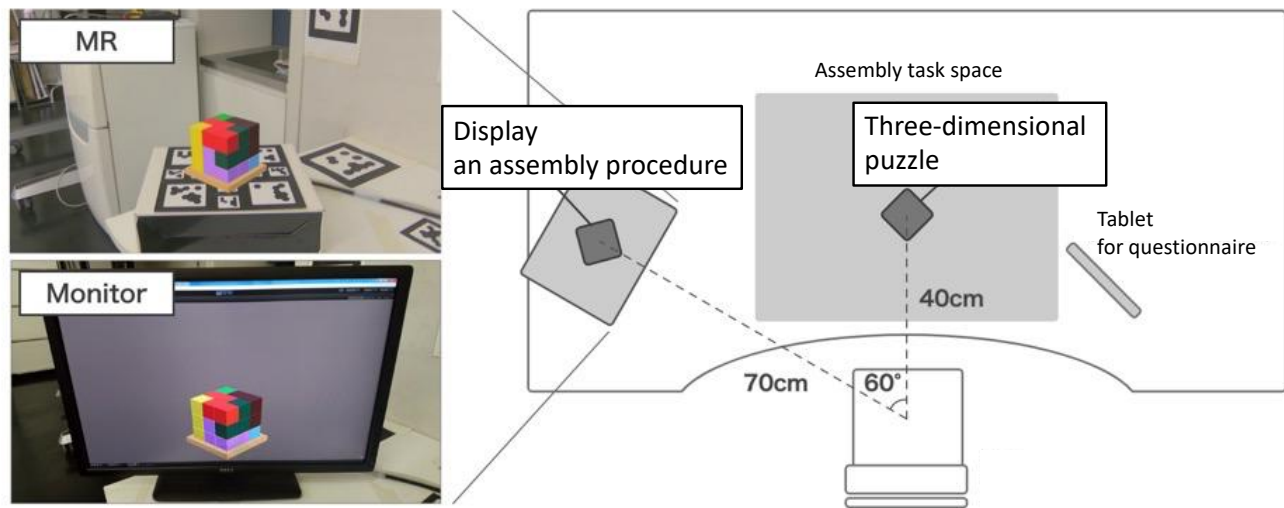


Figure 1. Layout of experiment

40 cm in front of the participants, and the assembly procedure was presented at a 70 cm distance and 60 degrees to the left. The displayed puzzle was set to the actual size and adjusted so that the diagonal lengths of the faces of the cube were the same under the MR and Monitor conditions.

### Measurements

As a subjective index, the Simulator Sickness Questionnaire (SSQ) was conducted before and after each section. In addition, a three-stage discomfort questionnaire was conducted every minute in the task: 1: Nothing at all, 2: Slightly Discomfort, 3: Very Discomfort.

As an objective index, data on the chest and abdominal respiration, and electrodermal activity (EDA) on the sole were obtained from sensors (Biosignals Plux). In addition, head tracking data was acquired from the HMD.

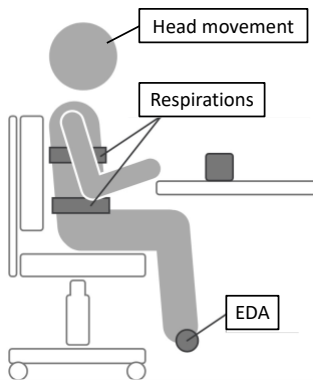


Figure 2. Measurement sensors

### Procedure

Participants were 12 university males with normal visual acuity. First, the purpose and method of the experiment were explained, and their consent was gained and put on various sensors. Then the HMD was attached and the interpupillary distance was measured and adjusted to the image clearly. The experimental trials consisted of a resting section of 3 minutes with the eyes closed, a task section of 15 minutes, and a recovery time of 3 minutes. Two trials of MR and Monitor conditions were performed in random order. A break of about 10 minutes was provided between the trials, and the recovery of the participants was confirmed.

## Results

### Subjective Index

The result of the score of the changes of the three-stage discomfort questionnaire is shown in figure 3. A two-way ANOVA was conducted, and the result showed a significant difference in the conditions factor ( $F(1, 11)=22.036, p=.001$ ), the time factor ( $F(14, 154)=8.375, p<.001$ ), and the interaction effects ( $F(14, 154)=9.991, p<.001$ ). Multiple comparisons showed a significant difference in the MR conditions (14 min > 1min, 2min,  $p<.01$ ), in the 4 min (MR > Monitor,  $p<.05$ ), and in the 5-15 min (MR > Monitor,  $p<.01$ ).

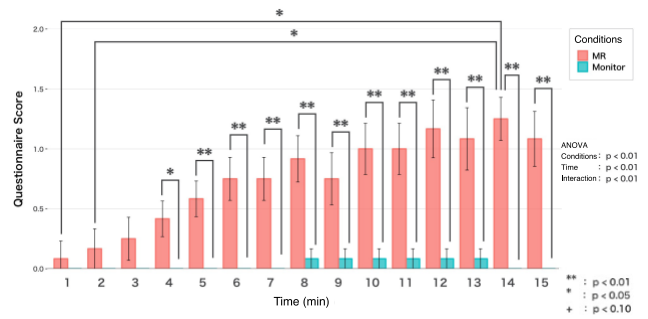


Figure 3. Result of Discomfort Questionnaire

### Objective Index

The result of the coefficient of variation of breath cycle time calculated from the abdominal respiration is shown in figure 4. A two-way ANOVA was conducted, and the result showed a significant trend in the conditions factor ( $F(1, 11)=4.168, p=.066$ ) and the interaction effects ( $F(14, 154)=1.706, p=.060$ ). Any significant differences were not found in the time ( $F(14, 154)=1.491, p=.120$ ). Multiple comparisons showed a significant difference in the 12-15 min (MR > Monitor,  $p<.05$ ).

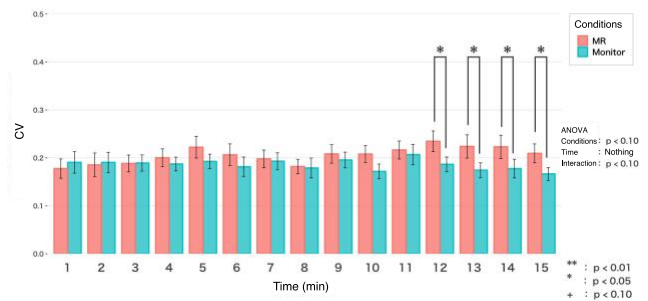


Figure 4. Result of Abdominal Respiration

The result of the skin conductance response (SCR) calculated from EDA is shown in figure 5. A two-way ANOVA was conducted, and the result showed a significant difference in the interaction effects ( $F(14, 154)=1.979, p=.023$ ). Any significant differences were not found in the conditions ( $F(1, 11)=1.074, p=.322$ ) and the time ( $F(14, 154)=1.060, p=.399$ ). Multiple comparisons showed a significant difference in the 14 min (MR > Monitor,  $p<.05$ ) and a significant trend in the 13 and 15 min (MR > Monitor,  $p<.10$ ).

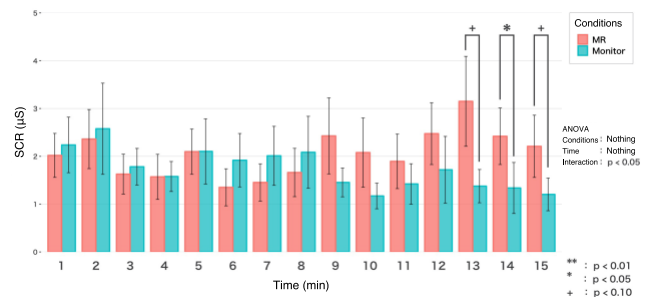


Figure 5. Result of Skin conductance response

### Estimation of Discomfort Level

For training and testing the deep learning model, the discomfort level was set as the target variable, and 9 variables of EDA, respiration, head position, and head rotation were set as explanatory variables. The data was used in MR conditions and excluded sections containing many missing and outliers of physiological indicators. In the deep learning model, the one-dimensional convolutional layer was three layers, and the fully connected layer was two layers.

The result of 4-fold cross-validation is shown in table 1 and the summary in table 2.

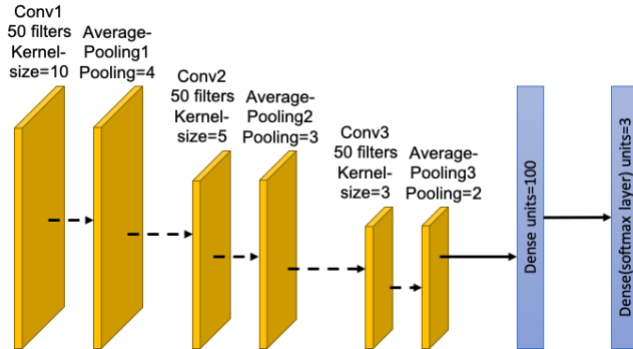


Figure 6. Deep Learning Model

Table 1. The confusion matrices of cross validation

		Discomfort Level	Prediction			
			1: Noting at all	2: Slightly Discomfort	3: Very Discomfort	
Cross Validation	1	TRUE	1	14	7	0
			2	2	10	4
			3	2	4	1
	2		1	14	7	0
			2	2	10	4
			3	2	4	1
	3		1	18	5	0
			2	4	6	2
			3	1	5	2
	4		1	6	3	3
			2	9	12	1
			3	2	4	3

Table 2. Evaluation index of deep learning model

		Prediction	Recall	F1-score
Discomfort Level	1: Noting at all	0.603	0.622	0.608
	2: Slightly Discomfort	0.549	0.574	0.555
	3: Very Discomfort	0.345	0.265	0.290

### Discussion

After about 10 minutes, the discomfort level was increased, and SCR and CV of abdominal respiration were increased under the MR conditions. These results mean that the same tendency was found in the changes of the psychological and physiological indicators. And the SCR is a transient indication of autonomic nervous system arousal in response to a stimulus as emotional arousal [2]. The SCR might be a predictor of discomfort level.

From the results of discomfort estimation using deep learning, a certain degree of accuracy was confirmed in estimating mild discomfort, but a low degree of accuracy in estimating severe discomfort. It was thought to be caused by a small amount of data. But detecting at an early stage of sickness is important to avoid discomfort, the physiological indicators obtained in this experiment are considered to have a certain degree of effectiveness.

### Conclusion

In this study, evaluating and estimating the discomfort level from physiological indicators with MR systems. The results suggest that mild discomfort can be detected with a certain degree of accuracy. The effectiveness predictor was might found in this study's physiological indicators. These are regarded that a sensor built in an MR headset could enable real-time feedback and encourage a break or something like that. However, it is necessary to improve the estimation accuracy, so to add another physiological indicator or estimating in other situations in future works.

### References

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### Author Biography

Yoshihiro Banchi is a Guest Junior Researcher in Waseda Research Institute for Science and Engineering. He received Ph.D., M.A. from Waseda University, in 2020, 2018. His research focuses ergonomics and data science on psycho-physiological effects in advanced technology, e.g. VR, XR, self-driving car.

*Kento Tsuchiya is a Bachelor of Science and Engineering at Waseda university. His research is to analyze e-sports tactics from a statistical point of view.*

*Masato Hirose is a 4th year undergrad in Waseda University, in Japan. His research focuses ergonomics in cutting edge technology, e.g. 3D, VR.*

*Ryu Takahashi is a Master's Student at Waseda University, Japan. He received B.A. in Human Sciences from Waseda University, in 2021. His research focuses ergonomics on psycho-physiological effects, especially simulator sickness, in advanced technology, e.g. VR, XR.*

*Riku Yamashita is a graduate student at Waseda University, Japan. He received B.A. from Waseda University in 2020. His research focuses applied statistics, e.g. sports data analytics, and meteorology. He is a member of Certified and Accredited Meteorologists of Japan from 2019.*

*Takashi Kawai is a Professor at Waseda University, Japan. He received Ph.D., M.A., B.A. in Human Sciences from Waseda University, in 1998, 1995, 1993. His research focuses ergonomics in immersion technologies, e.g. 3D, VR, XR. He is a Certified Professional Ergonomist. Currently he is in charging of Japan Committee Chair of Advanced Imaging Society, Executive Committee of International Ergonomics Association, and Conference Chair of Stereoscopic Displays and Application.*