

Multi-sensor-based Ambient Sensing System for the Estimation of Comfort/Discomfort to Lighting Condition During Desk Work

KENGO YOSHIMIZU^{1,a)} NORIKO TAKEMURA^{1,b)} YOSHIO IWAI^{2,c)} KOSUKE SATO^{1,d)}

Received: January 9, 2015, Accepted: April 3, 2015

Abstract: A multi-sensor-based ambient sensing system is proposed for estimating the user's comfort/discomfort in response to the lighting condition during desk work. The user's comfort/discomfort is estimated according to facial expression, body sway, writing motion and frequency of drinking measured by sensors embedded in the environment. The recognition rate of the user's comfort/discomfort under the lighting condition that induces different feelings of comfort depending on the user's state of the day is evaluated in an experimental environment. As a result, the recognition rate of the user's comfort/discomfort on a two-point scale is 91% when selecting a suitable combination of ambient sensors. Furthermore, it is suggested that not only information of facial expression but also the information of body sway, writing motion and frequency of drinking is useful for the estimation of comfort/discomfort.

Keywords: ambient sensing, multi-sensor system, estimation of comfort/discomfort, smart sensing technology

1. Introduction

Ambient sensing is an emerging field of research that aims to measure human behaviors or monitor the human state without the need for the subject to wear sensors. Various types of sensors are used in ambient sensing; e.g., cameras and depth sensors mounted on a wall or ceiling and sensors embedded in personal items such as in the case of a chair equipped with a pressure sensor or a cup having an embedded accelerometer. In contrast to body-mounted sensors such as an electroencephalograph or heart-rate monitor, an ambient sensor can measure transparently without constraining the user's natural movements. Therefore, ambient sensors are suitable for use in a practical system. Recently, a system that provides a service meeting individual needs by automatically recognizing the user's psychological state from ambient sensing data has attracted attention. The most important problem relating to the system is how to estimate the user's psychological state and user's situation. In particular, the user's comfort/discomfort is important information in providing a service yet is one of the most difficult indexes to estimate.

Comfort/discomfort estimation has been intensively researched in recent years. Most of the research has focused on physiological sensor information [1], [2], [3], [4]. Using a physiological sensor, a change in the user's state can be recognized without the

subject acting out a behavior. However, the user's natural movement is constrained because almost all physiological sensors are attached to the human body. An estimation method based on ambient sensor information has also been proposed [5], [6], [7]. Studies have investigated the estimation of discomfort felt under different lighting conditions according to information of the facial expression recognized in frontal facial images [8] and the relationship between writing speed measured using a vibration sensor attached to the back of a desk and the discomfort felt by a subject when blowing up a balloon [9].

In conventional research, only a single sensor is used to estimate comfort/discomfort. It thus seems that the comfort level can be estimated accurately only in the case that a strong stress stimulus is provided. In considering the application to practical systems in the future, it is important to estimate comfort not only in response to a strong stimulus that would make anyone uncomfortable but also in response to a weak stimulus that would invoke different feelings depending on the person. We are aiming to build a multi-sensor-based ambient sensing system that can estimate the user's comfort/discomfort even in a situation where the feeling of comfort will differ among individuals.

The proposed system is developed assuming a task of estimating comfort/discomfort of a user performing tasks while sitting at a desk in an indoor environment. The configuration space of the sensor is thus relatively small and it is unnecessary to consider movement or large postural change of the user. Additionally, as tasks performed in desk work are limited, useful data can be obtained from a small number of work-relevant sensors, such as chair and pen sensors. Furthermore, the effects of properties of the indoor environment such as illuminance or temperature on work efficiency are evaluated [10], [11], and it is expected that

¹ Graduate School of Engineering Science, Osaka University, Toyonaka, Osaka 560–8531, Japan

² Graduate School of Engineering, Tottori University, Tottori 680–8552, Japan

^{a)} yoshimizu@sens.sys.es.osaka-u.ac.jp

^{b)} takemura@sys.es.osaka-u.ac.jp

^{c)} iwai@ike.tottori-u.ac.jp

^{d)} sato@sys.es.osaka-u.ac.jp

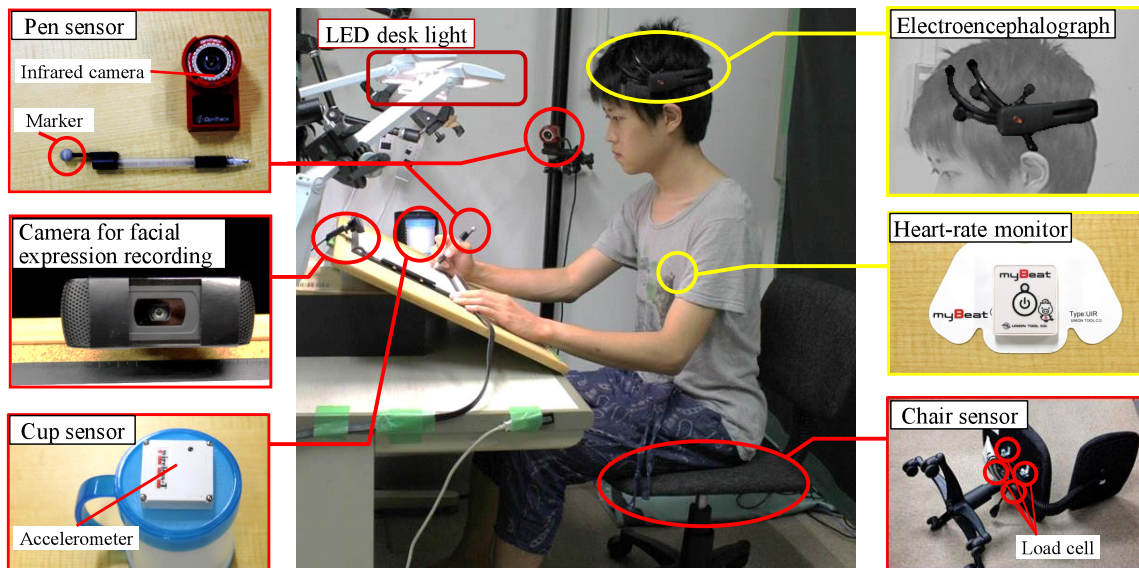


Fig. 1 System configuration: The chair is equipped with four load cells on the back. The pen is equipped with a retroreflection marker. The cup is equipped with an accelerometer on the back.

Table 1 Sensor details.

Sensor	Product name	Sampling rate	Data
Camera (Facial Expression)	HD Pro Webcam C910 /Logicool	1 Hz	RGB image (640 × 480 pixels)
Chair sensor	Ambient Chair [12]	10 Hz	The center of seating pressure
Pen sensor	OptiTrack Flex 3 /SPICE	100 Hz	The three-dimensional position
Cup sensor	WAA-001 /ATR-Promotions	5 Hz	Vertically upward acceleration of the cup
Electroencephalograph	Emotive EPOC /Emotive Systems	128 Hz	EEG signal of 14 electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF14) based on the International 10–20 locations
Heart-rate monitor	myBeat /Union tool	1,000 Hz	R–R interval (RRI)

estimations of the comfort/discomfort made by the proposed system can be used to improve the user’s work efficiency through automatic control of the indoor environment.

The user’s behavior during desk work, such as facial expressions, body sway, writing speed and frequency of drinking, appear to depend on the user’s comfort/discomfort. The proposed system thus measures the user’s behavior during desk work using a camera (for facial expression), chair sensor, pen sensor and cup sensor. In addition, an electroencephalograph and heart-rate monitor are used to allow comparison of the estimation result when only using ambient sensors with that when also using physiological sensors. Factors that affect discomfort in an indoor environment include illuminance and temperature. We estimate comfort in response to the lighting environment with high repeatability and reproducibility in an experiment.

2. System

This section describes the multi-sensor-based ambient sensing system used to estimate comfort/discomfort. The method of measuring the user’s state is described firstly in Section 2.1, and the method of estimating the user’s comfort/discomfort from the obtained sensor data is then described in Section 2.2.

2.1 Measurement of the User’s State

The user’s facial image is recorded with a camera, the center of seating pressure is recorded by pressure sensors of the chair, the three-dimensional position of the top of a pen is recorded using a marker on the pen, and the acceleration of a cup is recorded by an accelerometer in the cup; these sensors are considered ambient sensors. In addition, electroencephalography (EEG) signals and the R–R interval (RRI) are measured by an electroencephalograph and heart-rate monitor as a reference for comparing with the case of using only ambient sensors. The system configuration is shown in Fig. 1 and details of the sensors are given in Table 1.

2.2 Estimation of the User’s Comfort/Discomfort

Figure 2 is a flowchart of the estimation of comfort. Each process is detailed as follows.

2.2.1 Extraction of Feature Values

- **Camera (Facial Expression):** Facial feature points are extracted from the user’s facial image using Face Tracker API for real-time non-rigid face tracking [13]. The facial position, size and orientation are then normalized by homography transformation employing a facial recognition method [8]. Let $P = \{p_1, \dots, p_{12}\}$ be a set of normalized facial feature points (see Fig. 3). Let $d(p_a, p_b)$ ($p_a, p_b \in P$) be the Euclidean distance between two normalized facial

points. The following values are extracted.

- The distance between eyebrows:

$$D_1 = d(p_1, p_2)$$

- The distance between eye and eyebrow:

$$D_2 = \frac{1}{2}\{d(p_1, p_3) + d(p_2, p_4)\}$$

- The distance of eye-opening:

$$D_3 = \frac{1}{4}\{d(p_5, p_6) + d(p_7, p_8) + d(p_9, p_{10}) + d(p_{11}, p_{12})\}$$

- **Chair Sensor:** The amount of movement of the center position of the seating pressure is extracted from time-series data of the center positions measured by the chair sensor. The value is treated as the feature value of the chair sensor.
- **Pen Sensor:** The amount of movement of the top of the pen is extracted from time-series data of the three-dimensional position of the pen measured by the pen sensor. The value is treated as the feature value of the pen sensor.
- **Cup Sensor:** The angle of inclination of the cup is calculated from the vertical upward acceleration measured by the cup sensor. According to the angle, the user's state is classified as a state of handling the cup or a state of not handling the cup by threshold processing. The state of handling the cup relates to the action of drinking and the number of actions of drinking water is treated as the feature value of the cup.
- **Electroencephalograph:** The effects of artifacts in the observed EEG signal are eliminated by independent component analysis for each electrode. The denoised EEG signals

are filtered by band-pass filters of the delta wave (0.5–4 Hz), theta wave (4–8 Hz), alpha wave (8–14 Hz) and beta wave (14–38 Hz). The average power of each frequency bandwidth is treated as the feature value of the electroencephalograph; there are 56 (= 14 (electrodes) × 4 (waves)) feature values.

- **Heart-rate monitor:** The power spectrum density is estimated from RRI data. Let HF be the integral value of the power spectrum at high frequency (0.15–0.40 Hz). HF is treated as the feature value of the heart-rate monitor.

2.2.2 Normalization

Assuming a normal distribution, the extracted feature values are normalized with zero mean and a variance of 1 for each user's feature values by considering individual differences.

2.2.3 Learning and Recognition

Feature vectors are constructed from the normalized feature values, and the user's comfort/discomfort is learned and recognized from the feature vectors employing a support vector machine (SVM). SVM parameters include the penalty parameter *C* and kernel function parameter γ . In the learning process of the SVM, the optimal parameter *C* and γ are sought in a grid search.

3. Data Acquisition

In data acquisition, each subject was asked to perform an easy task under several lighting conditions, and the subject's state while performing the task was recorded by the sensors listed in Section 2. **Figure 4** shows the timetable. We conducted this experiment three times for each subject on different days. Details of data acquisition are described as follows.

- **Subjects:** Six Japanese subjects (four male and two female) who are right-handed and in their 20 s.
- **Lighting Conditions:** Tasks were performed under four lighting conditions (25, 750, 2,000, 5,000 lx on a desk surface) provided by four light-emitting-diode desk lights (MOS-L28/Matsuki Giken). During each task, the lighting condition was kept constant.

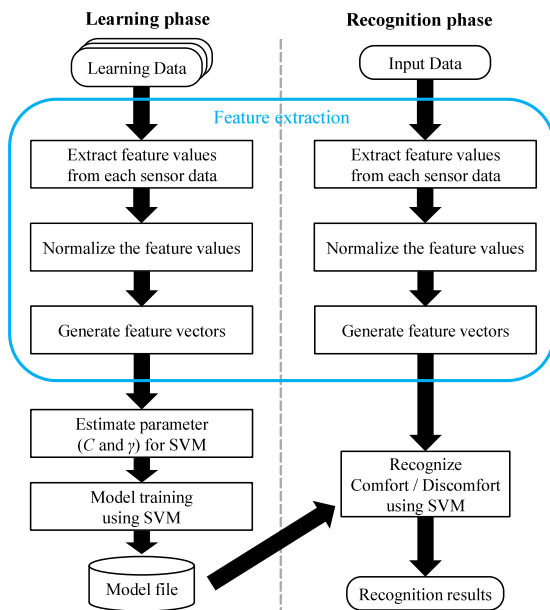


Fig. 2 Flowchart of the estimation of comfort.

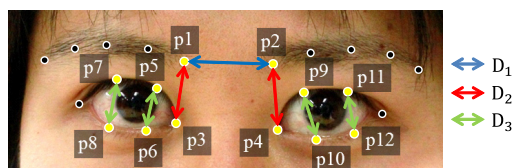


Fig. 3 Facial feature points around the eyes used to extract the feature value.

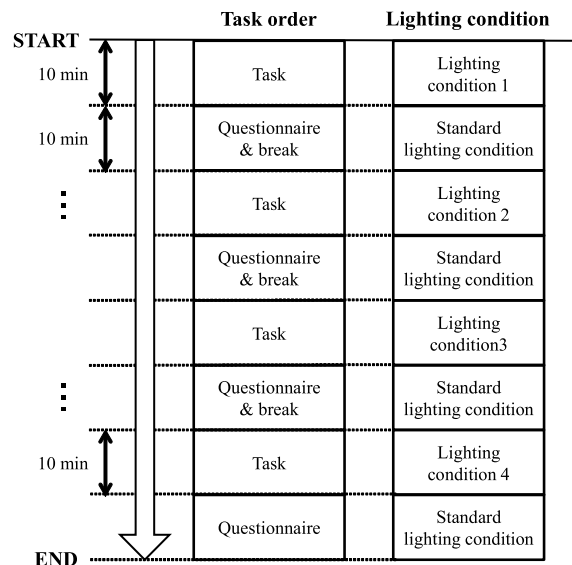


Fig. 4 Timetable: each subject was asked to perform the task under four different lighting conditions.

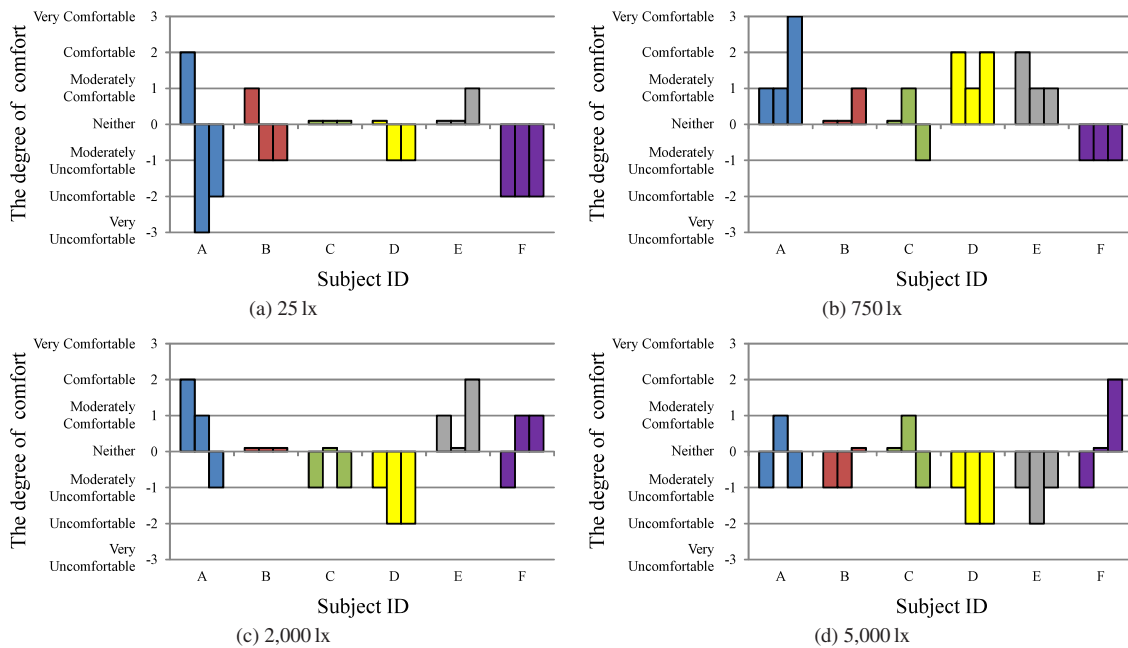


Fig. 7 Degree of comfort: (a)–(d) show the degree of comfort given in the questionnaire for each lighting condition. Three experiments are conducted for each subject. The figure shows the subjective evaluation of the comfort level in order of experiment.

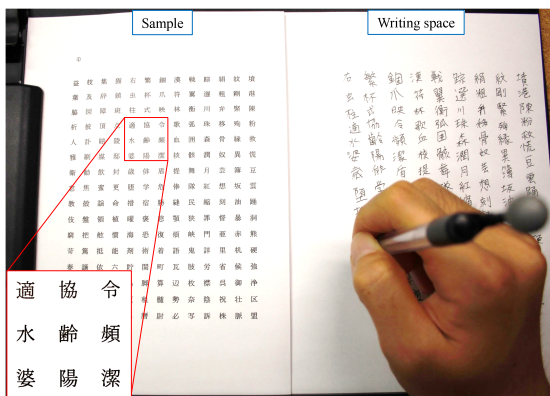


Fig. 5 Transcribing task.

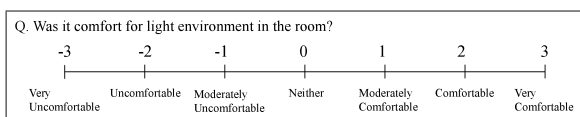


Fig. 6 Questionnaire about the subjective comfort level of the lighting condition.

The order of the lighting conditions was randomly changed for each subject. The illuminance during the break time between tasks was 750 lx to match a standard office lighting condition (Fig. 4: Standard lighting condition).

- **Task:** The task performed in data acquisition was transcribing Japanese kanji while looking at a sample. The scene of the task is shown in Fig. 5. Subjects performed each task for 10 minutes and then answered a brief questionnaire. Subjects were given a 10-minute break between tasks to mitigate the effects of the previous lighting condition.
- **Questionnaire:** After the end of each task, the comfort level was evaluated subjectively by the subject completing the questionnaire. Figure 6 shows the questionnaire item for the lighting condition at that time. The subjects selected a number along a seven-point scale from “-3” for very un-

Table 2 The number of feature vectors for each lighting condition.

25 lx	750 lx	2,000 lx	5,000 lx	total
942	837	1,020	948	3,747

comfortable to “3” for very comfortable.

3.1 Subjective Evaluation of the Comfort Level

Figure 7 shows the questionnaire result of the subjective evaluation of the comfort level. Each graph in Fig. 7 shows that the lighting condition induces different feelings depending on the subject. It was also confirmed that the comfort level is different even in the same person and the same lighting condition. As the comparison result of each subject, the ranges of subjective comfort level seem to differ widely in individuals.

3.2 Generation of Feature Vectors for Evaluation

Obtained sensor data are divided every 10 seconds into 4,320 data (= 6 (subjects) × 4 (conditions) × 10 (min) × 6 (data/min) × 3 (trials)). Using 3,747 data except those with missing values, feature vectors for the estimation of comfort/discomfort are generated employing the method described in Section 2. The number of feature vectors for each lighting condition is shown in Table 2.

4. Estimation of Comfort/Discomfort

Using the feature vectors generated in section 3, subjects’ comfort level was recognized employing the SVM-based method.

4.1 Comparison of Ambient Sensors with Physiological Sensors

The sensor selected from the following three sensor groups were used for comparison.

AMB: Ambient sensors (Camera (Facial expression), Chair sensor, Pen sensor and Cup sensor)

PHY: Physiological sensors (Electroencephalograph and

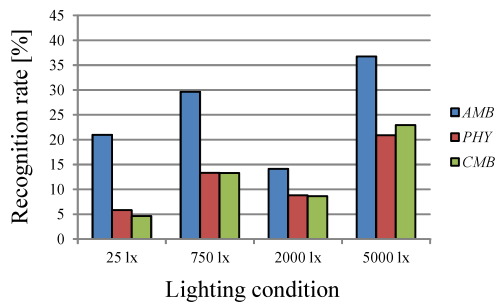


Fig. 8 The recognition rate of user’s comfort/discomfort on a seven-point scale for each lighting condition.

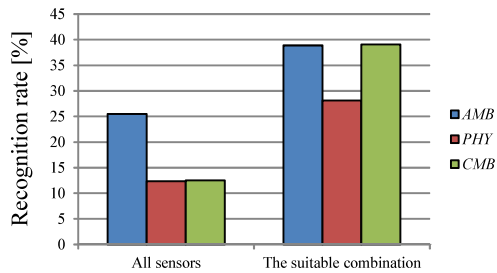


Fig. 9 The recognition rate in the case of selecting the suitable combination of sensors for each sensor group.

Heart-rate monitor) (as reference)

CMB: All sensors belonging to *AMB* and *PHY* (as reference)

Details of the evaluation method is described as follows.

4.1.1 Evaluation Method

The subjects’ comfort/discomfort was estimated employing the SVM-based method, using the feature vectors of 18 trials (= 6 (subjects) × 3 (trials)) for each lighting condition. Cross validation was conducted for each lighting condition, using feature vectors of one trial as testing data and those of fifteen trials from the other subjects was performed (5 (rest subjects) × 3 (trials)) as training data. The example of assignment is shown in Fig. 10 (a). In the case that there is not the same label (subjective comfort level) as testing data in training data, the result was excluded from evaluation.

4.1.2 Experimental Result and Discussion

Figure 8 shows the recognition rate for each lighting condition in the case of selecting all sensors in each sensor group. The recognition rate defined as the percentage of subjective comfort level on a seven-point scale recognized correctly. As a result of the comparison, it was confirmed that the recognition rate of *PHY* and *CMB* are lower than *AMB*. Generally, it is said that bioelectric signals fluctuate depending on user’s life rhythm or physical condition and include large individual differences. From this result, it was also confirmed that it is difficult to generate an accurate classifier from others’ data in the case of physiological sensor.

It seems that effective sensor is different depending on the situation, such as lighting conditions or characteristics of user. Improvement recognition rate was attempted by adaptively selecting sensors depending on the situation. In this experiment, the combination of the sensors with the highest recognition rate of all combinations was selected experimentally for each lighting condition. Figure 9 shows the average recognition rate of four lighting conditions in the case of selecting the suitable combination of sensors in each lighting condition. As a result of Fig. 9, it was

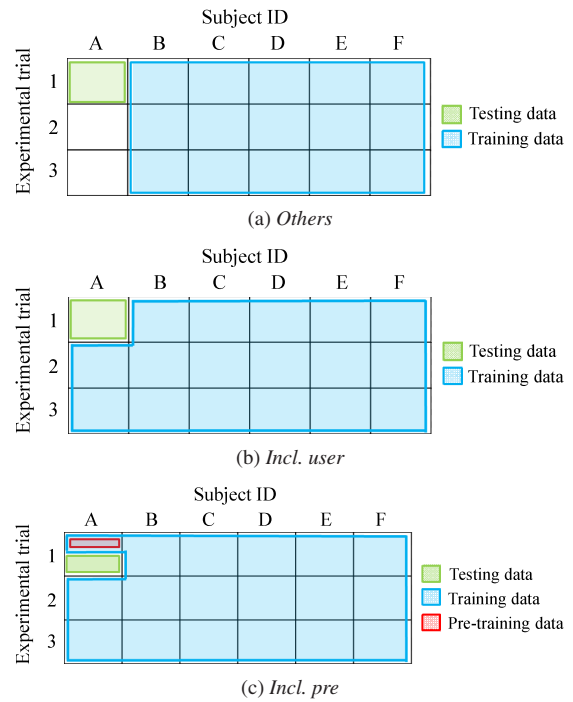


Fig. 10 The example of assignment in cross validation.

confirmed that improvement of recognition rate may be possible to selecting the sensor adaptively depending on the situation.

4.2 Comparison about Learning Conditions and Scale of Comfort/Discomfort

Available learning data or a scale of comfort/discomfort is different depending on where and how to use. Therefore, the recognition rate was evaluated in a variety of learning condition and scale of comfort/discomfort.

4.2.1 Evaluation Method

With respect to learning condition, the recognition rate was compared in the following three conditions.

Others: Only others’ data are used as training data (the same as Section 4.1) (see Fig. 10 (a)).

Incl. user: User’s data obtained the other day are used as training data in addition to *Others* (see Fig. 10 (b)).

Incl. pre: Pre-training data obtained on the day are used as training data in addition to *Incl. user*. The first half of a trial is used as training data and the second half of the trial is used as testing data (see Fig. 10 (c)).

With respect to a scale of comfort/discomfort, the recognition rate was evaluated in the following three scales that changed the scale on the basis of the seven-point questionnaire results of the subjects’ comfort.

7-scale: Comfort level is estimated on a seven-point scale ([−3] [−2] [−1] [0] [1] [2] [3]).

3-scale: Comfort level is estimated on a three-point scale ([−3, −2] [−1] [0, 1, 2, 3]).

2-scale: Comfort level is estimated on a two-point scale ([−3, −2, −1] [0, 1, 2, 3]).

Generally, the concept of comfort is classified into “comfort” and “pleasantness” [14]. In regard to the comfort of indoor lighting condition, however, “comfort” which is defined as “not discomfort” is used in many cases [8]. Therefore, the estimation of com-

fort on a multi-point scale sometimes is not needed in indoor environment. Additionally, a central tendency to avoid an extreme answer like “very uncomfortable” can be seen in the questionnaire result (see Fig. 7). Therefore, it is difficult to divide “very uncomfortable (-3)” and “uncomfortable (-2)” clearly. Considering the above, the comparative experiment was conducted in the above three scale.

4.2.2 Experimental Result and Discussion

Figure 11 shows the average recognition rate of four lighting conditions for each learning condition and for each scale. The suitable combination of sensors was selected experimentally for each learning condition for evaluating the recognition rate.

Focusing on PHY in Fig. 11, the recognition rate of Incl. user is higher than that of Others, and the recognition rate of Incl. pre is higher than that of Incl. user significantly. From this result, it seems that the value of the physiological sensor includes large individual differences and fluctuates greatly from day to day even if the same person. Though physiological sensors are effective in the case of Incl. pre, it is difficult to use in a practical system because of giving the physical load to mount sensors.

The fluctuation of the recognition rate of AMB is small compared with PHY. Even in the case of not conducting pre-training (Incl. user), the recognition rate of AMB are 52% when 7-scale, 72% when 3-scale and 79% when 2-scale. It is expected that the recognition rate is improved by increasing the number of

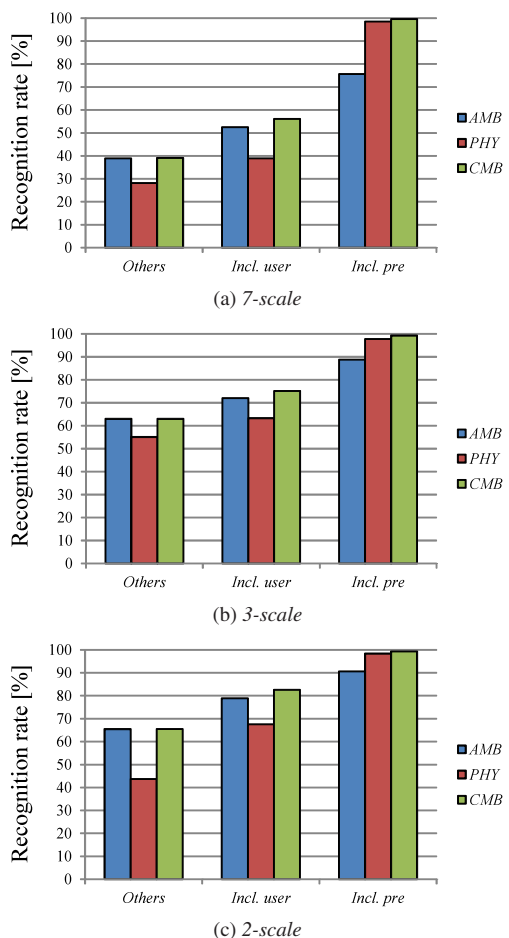


Fig. 11 The recognition rate for each learning condition and for each scale of comfort/discomfort.

training data in the future. If it is possible to use pre-training data (Incl. pre), the recognition rates are 76% when 7-scale, 89% when 3-scale and 91% when 2-scale. Since ambient sensors do not need to be mounted in contrast to physiological sensors, it is possible to conduct pre-training transparently by realizing a real time learning mechanism such as online learning.

4.3 Comparison of Multi-Sensor with Single Sensor

In the experiment, the recognition performance in the case of using multiple ambient sensors and a single ambient sensor was evaluated.

4.3.1 Evaluation Method

The recognition rate of Incl. pre was compared in the case of using the following sensors.

- The suitable combination in AMB selected experimentally
- All sensors in AMB
- Camera (Facial Expression)
- Chair Sensor
- Pen Sensor
- Cup Sensor

4.3.2 Experimental Result and Discussion

Figure 12 shows the average recognition rate of four lighting

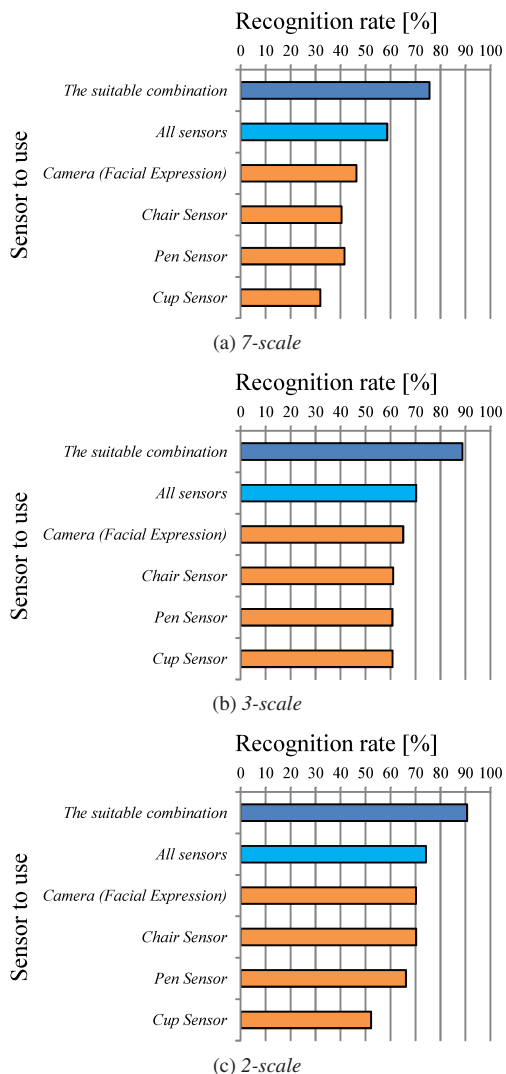


Fig. 12 The recognition rate in the case of multi-sensors and that of single sensors (when Incl. pre).

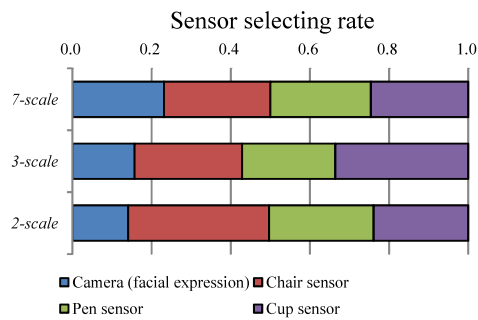


Fig. 13 Sensor selecting rate in the case of the suitable combination of sensors.

conditions in the case of using multi-sensors and single sensors. As a result of Fig. 12, it was confirmed that the recognition rate is improved in the case of using multi sensors compared with the case of using a single ambient sensor. In addition, the recognition rate of *The suitable combination* is significantly better than that of *All sensors*. Figure 13 shows the sensor selecting rate. The sensor selecting rate was defined as the rate of the number of times of selecting each sensor in the case of *The suitable combination*. If there are some candidates of the combination of sensors in the same recognition rate, the combination of small number of sensors was selected. According to Fig. 13, there are no sensors with extremely low selecting rate. Therefore, it is assumed that all ambient sensors contribute in the case of *The suitable combination*. It was suggested that the information of facial expression, body sway, writing motion and frequency of drinking is useful for estimating comfort/discomfort.

5. Conclusions and Future Works

In this paper, we built a multi-sensor-based ambient sensing system for the estimation of comfort/discomfort during desk work. The recognition rate of the user's comfort/discomfort under the lighting condition that induces different feelings of comfort depending on the user's state of the day is evaluated in an experimental environment. As a result, it was confirmed that the highest recognition rate of the user's comfort/discomfort on a two-point scale is 91% by selecting the suitable combination of ambient sensors in the case of using pre-training data. Pre-training without user awareness seemed to be possible by realizing a real time learning mechanism such as online learning. In addition, compared with the experimental results of single sensors, it was suggested that the information of facial expression, body sway, writing motion and frequency of drinking is useful for estimating comfort/discomfort. The proposed system is suitable for using in an office environment. If it is possible to achieve a comfortable lighting environment by controlling lighting condition based on estimated comfort level, it would lead to enhance user's work efficiency by increase of concentration.

From the experiment, it was confirmed that the performance of comfort/discomfort estimation is improved significantly by selecting the suitable combination depending on the situation. The future issue is how to select the optimal sensor adaptively on the situation. We consider that it is possible to select effective sensors by employing the algorithm of machine learning such as sparse learning or boosting learning. Furthermore, we will verify

whether our findings can be applied to the estimation of comfort felt in response to the thermal environment and acoustic environment by conducting additional experiments. Although this proposed system was only applied to a task of writing on paper, we will expand the system so that it can be applied to both paper and computer work in practical environments of desk work.

References

- [1] Kumar, M., Neubert, S., Behrendt, S., Rieger, A., Weippert, M., Stoll, N., Thurow, K. and Stoll, R.: Stress Monitoring Based on Stochastic Fuzzy Analysis of Heartbeat Intervals, *IEEE Trans. Fuzzy Systems*, Vol.20, No.4, pp.746–759 (2012).
- [2] Healey, J. and Picard, R.: SmartCar Detecting Driver Stress, *International Conference on Pattern Recognition*, Vol.4, pp.218–221 (2000).
- [3] Ide, H., Lopez, G., Shuzo, M., Mitsuyoshi, S., Delaunay, J.-J. and Yamada, I.: Workplace Stress Estimation Method based on Multivariate Analysis of Physiological Indices, *International Conference on Health Information*, pp.53–60 (2012).
- [4] Hosseini, S.A., Khalilzadeh, M.A. and Changiz, S.: Emotional Stress Recognition System for Affective Computing Based on Bio-Signals, *Journal of Biological Systems*, Vol.18, pp.101–114 (2010).
- [5] Kappor, A., Bursleson, W. and Picard, R.W.: Automatic Prediction of Frustration, *International Journal of Human-Computer Studies*, Vol.65, No.8, pp.724–736 (2007).
- [6] Gunes, H. and Piccardi, M.: Bi-Modal Emotion Recognition from Expressive Face and Body Gestures, *Journal of Network and Computer Applications*, Vol.30, No.4, pp.1334–1345 (2007).
- [7] Lv, H.-R., Lin, Z.-L., Yin, W.-J. and Dong, J.: Emotion recognition based on pressure sensor keyboards, *International Conference on Multimedia and Expo*, pp.1089–1092 (2008).
- [8] Kitamura, K., Takemura, N., Iwai, Y. and Sato, K.: Automatic Detection of Unconscious Reactions to Illuminance Changes in Illumination, *Articulated Motion and Deformable Objects*, pp.134–143, Springer Berlin Heidelberg (2012).
- [9] Hamaguchi, N., Yamamoto, K., Iwai, D. and Sato, K.: Estimation of Subjective difficulty and Psychological Stress by Ambient Sensing of Desk Panel Vibrations, *SICE Journal of Control, Measurement, and System Integration*, Vol.5, No.1, pp.2–7 (2011).
- [10] Yasukouchi, A., Nan, Q., Toda, N. and Noguchi, H.: The effect of the CCT and illuminance level control of light in daytime on performance and circadian rhythm, *2012 Annual Conference of IEIJ* (2012).
- [11] Seppanen, O., Fisk, W.J. and Faulkner, D.: Cost benefit analysis of the nighttime ventilative cooling in office building, *Proc. Healthy Buildings 2003*, pp.394–399 (2003).
- [12] Wataya, R., Iwai, D. and Sato, K.: Ambient sensing chairs for audience emotion recognition by finding synchrony of body sway, *The 1st IEEE Global Conference on Consumer Electronics*, pp.29–33 (2012).
- [13] Lucey, S., Wang, Y., Saragih, J. and Cohn, J.: Non-rigid Face Tracking with Enforced Convexity and Local Appearance Consistency Constraint, *International Journal of Image and Vision Computing*, Vol.28, No.5, pp.781–789 (2010).
- [14] Mudri, L. and Lenard, J.D.: Comfortable and/or pleasant ambience: conflicting issue, *International Conference on Passive and Low Energy Architecture*, pp.599–604 (2000).



Kengo Yoshimizu received his B.S. and M.S. degrees from Osaka University, Japan, in 2013 and 2015, respectively. He is with Kubota Corporation, Osaka, Japan. His research interests include ambient intelligence.



Noriko Takemura received her B.Eng., M.Eng., and Ph.D. (Eng.) degrees from Osaka University, Osaka, Japan, in 2006, 2007, and 2010, respectively. In 2010, she joined the Osaka University as a Research Fellow. She is now an Assistant Professor at Osaka University since 2014. Her research interests include pattern recognition and environmental intelligence.



Yoshio Iwai graduated from Osaka University in 1992 and completed his M.Sc. and doctoral programs in 1994 and 1997, respectively. He was then appointed a Research Associate at the university, subsequently becoming an Associate Professor. From 2004 to 2005, he was a Visiting Researcher at Cambridge University. He is

currently a Professor in the Graduate School of Engineering at Tottori University. He is engaged in studies related to computer vision. He is a member of IEEE, the Information Processing Society, and Japanese Robotics Society. He holds a D.Eng. degree.



Kosuke Sato received his B.Sc., M.Sc., and Ph.D. degrees from Osaka University, Japan, in 1983, 1985, and 1988, respectively. He was a Visiting Scientist at the Robotics Institute, Carnegie Mellon University, from 1988 to 1990. He is currently a Professor in Graduate School of Engineering Science, Osaka University.

His research interests include image sensing, 3D image processing, digital archiving, and virtual reality.