**VHF4-1**
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# Perception-based Non-contact Sensor used Emotion Estimation Technique and Its Application Possibility

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Keywords: Emotion Estimation, Non-contact Sensor, Human Perception, Internet of Things (IoT).

**ABSTRACT**

*This paper presents the customized emotion estimation system for individuals based on indoor environment data regarding human perception and its application possibilities. Our system estimates emotions without camera sensor or wearable sensors. Experiment results show that our system achieved over 80% estimation accuracy, thereby demonstrating the effectiveness of our system.*

## 1 Introduction

Recently, emotion estimation techniques are becoming popular in terms of reforming work style supporting class, supporting drivers, and providing individual optimal services [1]-[3]. One of the effective approaches for emotion estimation is to use an image or video data. Hossain et al. captured speech and image signals of a participant in a smart home scenario for emotion detection [2]. Okada et al. estimated emotion from physiological signals such as RR intervals and blood volumes obtained by analyzing hemoglobin concentrations from facial color images [3]. The work in [3] showed that facial image data was effective for emotion estimation. However, considering privacy issues, it is desirable to estimate emotion without image or video data.

Wearable devices, which acquire vital data, have been the other traditional alternative to estimate participant's emotions. Although vital-sensors used emotion estimation can achieve high estimation accuracy, persons must wear the measurement device, limiting human behaviors.

The Internet of Things (IoT)-inspired data sensing is also expected for detecting emotion and improving our life. From the idea of Society 5.0, as proposed by the Japanese Government, combining various types of data obtained using the IoT with machine learning and big data analysis enables us to solve social issues. It is expected that the idea of Society 5.0 will enable us to estimate emotions without the need for camera sensors or wearable devices. However, it has been challenging to specify data set in estimating emotions. Komuro et al. proposed a customized emotion estimation system for individuals based on non-contact sensor data regarding human perceptions [5]-[7].

This paper presents our proposed customized emotion estimation model for individuals based on collected indoor environment data regarding human perception. Our system estimates individual emotions without image data from camera sensors or vital data from wearable sensors. The experimental results show that the proposed method achieved over 80 % estimation accuracy by using multiple types of sensors, thereby demonstrating the effectiveness of the proposed system. This paper also introduces the application possibility of our emotion estimation system.

## 2 System Model Experiment

Figure 1 shows the structure of our system. Our system collects and saves indoor environment data, and sensor nodes measure environmental data regarding human perceptions. After that, sensor nodes send the measured data to the coordinator node. The coordinator node then transfers the received data from the sensor nodes to the data logger. The data logger then logs the data from the sensor node and sends them to the cloud server. Vital and emotion data obtained using the NEC Emotion Analysis Solution [4] are saved on the cloud server, which is then used as correct answer data for machine learning.

We developed indoor environment sensors regarding human perception (personal sensors), indoor environment sensors (indoor sensors), and point-based thermography sensors.

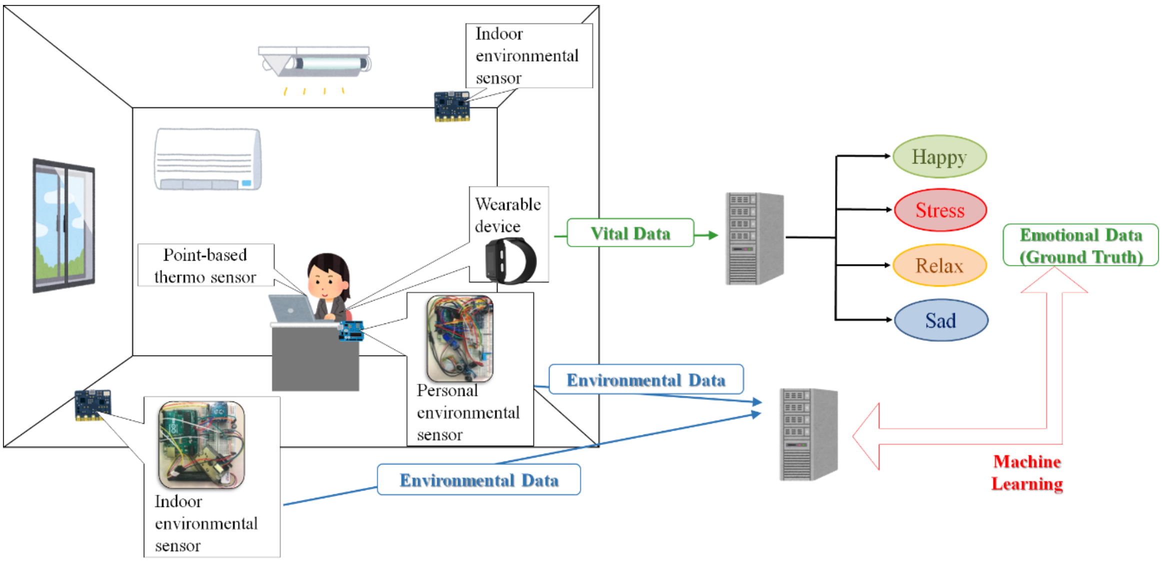


**Fig. 1 System model**

A personal sensor obtains temperature ((Degree Celsius), humidity (%), illuminance (lux), odor intensity (1 to 1023), distance (cm), human detection (0 or 1), blue light intensity (1 to 1023), and sound intensity (dB). An indoor sensor obtains CO2 concentration (ppm), dust concentration ($\mu gm^3$), and air pressure (hPa). A point-based thermography sensor measures temperature around the sensor and sends the measured data (Degree Celsius) as 8x8 points data. Point-based thermography sensors can be used for measuring humans' surface temperature. The server saves the collected data as CSV files. The files include measured data, sensor ID, and sensor data reception time.

Individual emotions are estimated from obtained indoor environmental data. Emotions are estimated using machine learning methods. At the data collection phase, indoor environment data are collected from the developed personal and indoor environment sensors.

The phase of estimating emotions from vital sensors draws on the report in [4]. The Emotion Analysis System [4] analyzes the balance between the sympathetic nerve and the parasympathetic one, the measured skin temperature, and heart rate. Then the arousal and valence levels are determined based on the analysis results. It then classifies into the following four types of emotions based on the levels: HAPPY, STRESSED, SAD, and RELAXED.

Our system estimates emotions with machine learning methods. Our system uses collected environmental data from personal, indoor, and point-based thermography sensors and emotion data from Emotion Analysis System [4], which is used as the correct answer. Environment sensor data are linked with individual emotions obtained from the emotion analysis method [4], which are measured during working in the experiment room.

## 3 Experiment Results

Our system logged the environment data, four types of emotions, and their reception time over a period of 60 days. Our system used 70 % as training data and the remaining 30 % as test data. Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and Neural Network (NN) were used for emotion estimation models.

Tables 1 to 4 shows the parameter settings for each machine learning method. Parameters not listed in the Tables 1 to 4 are the default values of each library. Machine learning parameters used in this study are obtained by grid searching.

**Table 1 Parameter setting for KNN**

| Parameter | Value |
|---|---|
| n_neighbors | 6 |

**Table 2 Parameter setting for RF**

| Parameter | Value |
|---|---|
| max_depth | 30 |
| n_estimators | 30 |

**Table 3 Parameter setting for GBST**

| Parameter | Value |
|---|---|
| num boost round | 100 |
| early stopping rounds | 100 |
| feature fraction | 0.8 |

**Table 4 Parameter setting for NN**

| Parameter | Value |
|---|---|
| batch size | 128 or 512 |
| Epochs | 1000 |
| Num Intermediate Layers | 3 |
| Num Intermediate Layer's Outputs | 50 |
| Intermediate Layer's activation | relu |
| OutputLayer's activation | softmax |

Figure 2 shows the estimation accuracy for each method. It is seen from Fig. 2 that the RF and GBDT method showed the highest estimation accuracy, which shows that the effectiveness of decision tree-based machine learning methods. The estimation accuracy can achieve over 80% by using decision tree-based machine learning methods.

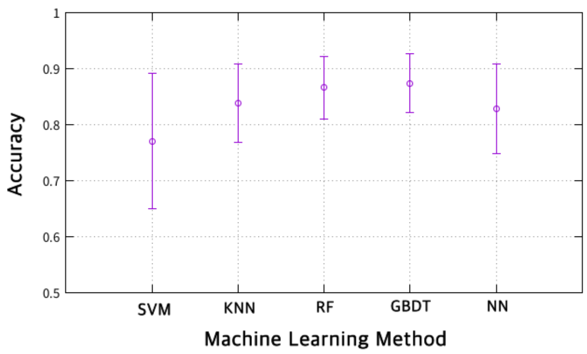

**Fig. 2 Estimation accuracy**

Table 5 shows the importance of each sensor for four subjects. The importance of CO2 concentration ranks the highest among the sensors, regardless of the person analyzed. This result implies that the CO2 concentration can affect emotion. Because a point based thermo sensor can obtain the fluctuation of face-temperature, the importance of a point based thermo sensor was relatively high. In addition, the distance sensor also showed relatively high importance because a distance sensor probably obtains unconscious movements due to psychological factors. The importance of other sensor data depends on the persons analyzed.

Lots of literature have reported the relationships between emotion and physical data such as odor, sound, lighting, and CO2 concentration. Bombail introduced that conversely odours can also affect animal/human emotions by inducing a stress response [8]. Ayash et al. reported that student emotion and performance in learning environments were affected by illumination intensity and level [9]. Noguchi et al., investigated and found the relationship between the emotional state, respiratory rate, tidal volume, minute ventilation, and CO2 concentration [10]. Our personal and indoor sensors can measure multi-modal data, including the above odor, sound, lighting, and CO2 physical data regarding emotion. Our measured data and emotion predictions are implicitly supported by such conventional researches.

**Table 5 Importance of each sensor**

| Person ID | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| CO2 Concentration | 0.149 | 0.151 | 0.158 | 0.133 |
| Thermography | 0.103 | N/A | N/A | 0.083 |
| Temperature | 0.019 | 0.100 | 0.095 | 0.099 |
| Distance | 0.101 | 0.076 | 0.090 | 0.079 |
| Loudness | 0.063 | 0.069 | 0.084 | 0.060 |
| Illuminance | 0.080 | 0.061 | 0.055 | 0.067 |
| Odor Intensity | 0.073 | 0.086 | 0.102 | 0.065 |
| Humidity | 0.014 | 0.067 | 0.058 | 0.062 |
| Infrared ray | 0.069 | 0.059 | 0.058 | 0.062 |
| Blue Light Intensity | 0.085 | 0.103 | 0.082 | 0.076 |
| Dust Concentration | 0.062 | 0.058 | 0.062 | 0.062 |
| Atmospheric Pressure | 0.068 | 0.062 | 0.050 | 0.046 |
| Human Detection | 0.039 | 0.043 | 0.090 | 0.042 |

## 4 Application Possibility

Our obtained result that our system can determine emotion with high accuracy from environmental data is helpful for future research approaches. Visualizing environment data obtained by our sensors and emotion data can make us understand the relationship between mental-condition propagation and environment conditions or persons without camera sensors or wearable devices, as shown in Fig. 3. In addition, combining our system and virtual reality techniques provides us various application services, such as realistic theater/museum considering individual emotion and dangerous occupations training considering the individual mental condition. So, there is a possibility that the obtained results contribute to building a less stressful environment.

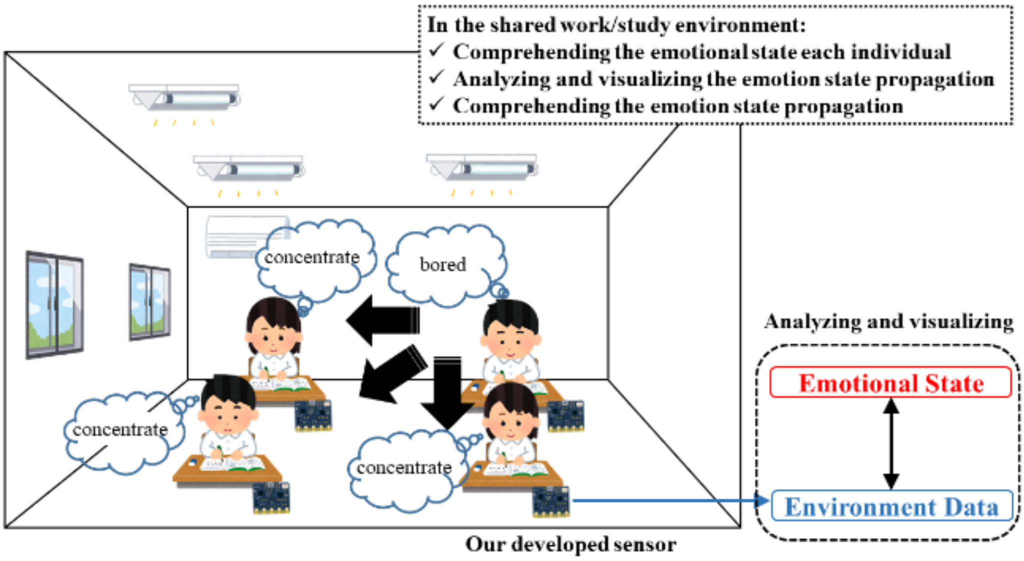


**Fig.3 Visualizing and understanding emotional state propagation**

## 5 Conclusions

This paper presented the customized emotion estimation system for individuals based on indoor environment data regarding human perception and its application possibilities. Our system estimated emotions without image data from camera sensor or vital data from wearable sensors. Experiment results showed that our system achieved over 80% estimation accuracy, thereby demonstrating the effectiveness of our system.

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