Development of metabolic rate prediction model using deep learning via Kinect camera in an indoor environment

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Abstract. Currently, there are only a few conventional methods to measure individual factors affecting metabolic rate (MET) based on the thermal comfort of occupants in residential buildings. In this work, a deep learning based MET prediction using a Kinect camera, which is a non-contact sensor, was developed. The root mean squared error (RMSE) and the coefficient of variation (CV) of the RMSE were used as indicators to predict MET accuracy. A total of 31 subjects participated in the experiment (16 men and 15 women). The METs of eight representative activities in the ASHRAE Standard 55 were measured (lying down, sitting, cooking, walking, eating, house cleaning, folding clothes, and handling 50 kg of books). The predicted results for all eight activities were significantly high. (RMSE: 0.26, CV: 13%). Further, METs were analyzed according to the gender and body mass index (BMI). Results of the analysis based on gender reveal that METs of men are higher than those of women. Analysis based on BMI showed that MET increased with higher BMI. However, with respect to sitting and eating food, the higher the BMI, the lower is the MET. This paper suggest that, a creative method was developed herein for predicting MET in an indoor environment with fairly high accuracy. Moreover, the difference in MET considering behavior as a factor was analyzed according to gender and BMI; these results can be used to develop guidelines for more accurate thermal comfort control.

1. Introduction

The indoor residence time of humans has increased by 85–90%, and many studies have been conducted to improve the indoor environment quality (IEQ) for people [1]. Thermal comfort (TC) is an important component of the IEQ, which not only directly affects the health of occupants but also affects work efficiency and productivity [2, 3]. Fanger's predicted mean vote (PMV) model is the most commonly used indicator of TC. The PMV model was created through experiments in a chamber with a heat balance principle and steady-state conditions [4]. The factors that affect the PMV are thermal environmental factors, such as air temperature, mean radiant temperature (MRT), relative humidity (RH), and air velocity, and individual criteria such as clo and metabolic rate (MET) [5, 6]. Environmental factors can be measured using simple sensors. However, in the case of personal factors, it is difficult to acquire data because it changes from person to person, and the equipment are very expensive [7, 8].

Many studies in the subject of construction, suggests PMV controlled methods of heating, ventilation, and air conditioning (HVAC) system to improve TC.

Moon et al. developed an advanced thermal control method in residential building based on Artificial Neural Network (ANN) for PMV control [9]. The variables used are air temperature, humidity, and PMV control variables. However, in the PMV variable, MET was defaulted to 1 and clo value was set to 1 in winter and 0.5 in summer [10]. Model predictive control (MPC) algorithms for PMV control have been developed, which propose a method to minimize energy consumption while maintaining thermal comfort by Chen et al. [10]. Chen also incorrectly used the default value of 1 as the MET value and 0.71 as the clo value. As such, it is a common practice in recent studies to evaluate personal factors of occupational settings as default values. However, according to Luo et al. the most significant component of the TC evaluation factor is MET, which should not be evaluated roughly [11]. Therefore,
in this study, for more precise PMV control, the authors developed and verified a method to precisely predict the MET, which has the greatest influence on the TC among the personal factors.

2. Methods
2.1. Experimental method.
The methodology of this experiment is shown in Fig. 1. Firstly, the authors used Kinect cameras at the Sensing level to observe subjects' diverse life activities, and at the same time, occupational biometric information from Fitbit ™ (Wearable Device) was acquired. Then the AI was allowed to learn image information and metabolic information about behavior. Based on the AI's accumulated database, MET could be predicted with Kinect camera without the help of any wearable device.

![Figure 1. Concept of MET prediction](image)

The method description of this study is shown in Fig. 2. First, a Kinect camera was used to sense human activities. This made it possible to acquire 5 RGB images per second from the Kinect camera. At the same time heart rate data from Fitbit ™ (Wearable device) was collected. The MET value was then calculated according to the international metabolism standard ISO 8996 using the input heart rate data and the unchanged information (gender, weight, and age) of the subject. Deep learning was performed in the AI System using the MET value calculated by the Level 3 method of ISO 8996 and the RGB images obtained by the Kinect camera. Ultimately, without the help of a wearable device (Fitbit ™), a person's MET could be predicted with a Kinect camera, a non-contact sensor.

![Figure 2. Mechanism of MET Prediction](image)

2.2. Experiment conditions
The experiment was conducted at Room 505, Yonsei University Engineering Building, Seoul, Korea (Fig 3. is the floor plan). The increase in \( CO_2 \) concentration caused by laboratory activities in the room
could affect the MET, so the door was opened, and the experiment was carried out with $CO_2$ concentration below 1000 PPM. All glass walls were blinded to protect the privacy of the subjects.

Figure 3. Floor plan of the experiment room.

Table 1 shows the laboratory conditions. The temperature was 23.7 °C ± 1.09 and the relative humidity was 36.8% ± 9.06.

Table 1. Conditions of the experiment room

| Room condition | Air temperature (°C) | MRT (°C) | Relative humidity (%) | Air velocity (m/s) |
|----------------|----------------------|----------|-----------------------|--------------------|
|                | 23.72 ± 1.09         | 23.11 ± 0.87 | 36.84 ± 9.06         | 0.04 ± 0.04       |

A total of 31 subjects participated. The subjects were chosen such that they were all physically and mentally healthy to perform the various activities required in this experiment. Table 2 Shows the gender, age, height, weight, and body mass index (BMI) information collected from the subjects.

Table 2. Demographic information of the participants

|                | Total (31) | Men (16) | Women (15) |
|----------------|------------|----------|------------|
| Age            | 25.4 ± 2.4 | 26.2 ± 2.5 | 24.6 ± 2.2 |
| Height (cm)    | 169.7 ± 9.12 | 176.8 ± 6.0 | 162.0 ± 4.5 |
| Weight (kg)    | 64.6 ± 14.6 | 75.2 ± 12.6 | 53.2 ± 5.1 |
| BMI (kg/m²)    | 22.2 ± 3.6 | 24.1 ± 3.9 | 20.3 ± 1.9 |

2.3. Experimental contents

In this study, eight typical indoor activities were selected among the typical tasks presented in ASHRAE standard 55 (lying down, sitting, cooking, walking, eating, house cleaning, folding clothes, and handling 50 kg of books) [12]. The order of experiments proceeded from low intense activity to high in order to minimize the effect of one activity on its preceding activity. Since the experiment was conducted for 15 minutes per activity for eight behaviors, the total experimental time for one subject was 120 minutes. To minimize the impact of previous activities on the following activities, data for 1 minute after the start of each activity and 2 minutes before the end of each activity were not considered. The remaining 12 minutes of data were divided into 10 parts, and 70% of it was used as learning data and 30% as test data.
Table 3. Experimental procedure.

| Activities                  | (1) Lying down  | (2) Sitting (reading book) | (3) Cooking (no heating) | (4) Walking Slow |
|-----------------------------|-----------------|----------------------------|--------------------------|------------------|
| (5) Eating (coffee & bread) |                 |                            |                          |                  |
| (6) House cleaning          |                 |                            |                          |                  |
| (7) Laundry, folding clothes|                 |                            |                          |                  |
| (8) Handling 50kg of books  |                 |                            |                          |                  |

3. Results and Discussion

3.1. Predicted accuracy comparison

The root mean squared error (RMSE) and the coefficient of variation (CV) are considered as the most appropriate indicators for MET prediction using deep learning. RMSE and CV are mainly used as accuracy evaluation index when predicting building air-conditioning energy using AI in ASHRAE guideline 14 [12]. RMSE is a measure of the difference between Predicted MET and ground truth MET, while RMSE is a measure of the standard deviation and can be used to objectively evaluate the difference in value from the mean and is always a positive number. CV is a percentage value, and the closer it is to 0%, higher is the prediction accuracy [13]. The RMSE and CV are summarized for eight behaviors in Table 4.

Table 4. RMSE, CV (RMSE) summary of 31 subjects by eight behaviors

| Activities                  | Lying down RMSE 0.11±0.1 | Sitting (reading books) RMSE 0.15±0.08 | Cooking (no heating) RMSE 0.24±0.23 | Walking slowly RMSE 0.23±0.12 | Eating (coffee & bread) RMSE 0.24±0.1 | House cleaning RMSE 0.28±0.17 | Laundry, folding clothes RMSE 0.27±0.12 | Handling 50kg of books RMSE 0.28±0.2 |
|-----------------------------|---------------------------|----------------------------------------|-------------------------------------|-------------------------------|--------------------------------------|-----------------------------|----------------------------------------|----------------------------------------|
| CV                          | 10.2%                     | 12.1%                                  | 15.1%                               | 13.1%                         | 12.8%                                | 12.5%                       | 9.7%                                   | 8.7%                                   |

3.2. Comparison of measured MET results by gender

First, the authors hypothesize that there is a difference in MET between men and women. Statistical analysis showed that there was a difference in MET according to gender in all behaviors (P-value <0.001) except for cooking (P-value = 0.881) among the eight behaviors. The comprehensive features are summarized in Fig. 4.

(1) For lying down, MET of men was higher. This is thought to be due to the high basal metabolic rate (BMR) of men.

(2) The METs of men are generally high for house cleaning, folding clothes, and handling 50 kg of books.

(3) However, for sitting (reading book) and eating, women’s METs were higher.

(4) Comprehensively, it cannot be said that all behaviors have a MET with a high specific gender. However, at higher activity levels, the men’s MET values were higher.
3.3. Comparison of measured MET results with BMI

The BMI is an important physiological factor affecting thermal sensation [14]. In particular, analysis of the BMI is often more significant than gender analysis as men generally have a higher BMI than women. A total of 31 participants were classified into three levels of BMI: Level 1 (10 subjects, BMI: 18.1–20.2), Level 2 (11 subjects, BMI: 20.4–22.0), Level 3 (10 subjects, BMI: ).

The results of a comparison of MET by BMI for each activity are shown in Fig. 5. MET analysis results for all the behaviors are statistically significant according to the BMI, except for house cleaning (P-value = 0.343). The results of the analysis are as follows:

1. There is no significant difference according to BMI by activity level for lying down.

2. (Level 2) For the sitting activity, BMI and MET are negatively correlated, which means that if a slender person and an obese person are sitting together, the slender person consumes a lot of calories, whereas the obese person consumes relatively less calories.

3. Activity level for eating has a low MET for those with high BMI. This means that when consuming the same food, slim people consume more calories than obese people.

4. For folding clothes and handling 50 kg of books, which have relatively high MET values, the higher the BMI, the greater is the difference in MET. This means that a person with a high BMI will have high MET and consume more calories when exercising with a certain intensity.
4. Conclusion

In the conventional PMV control, MET was the default value because it was difficult and expensive to measure. Therefore, this study suggests a breakthrough method can reflect the MET value in real time. Even if the number of subjects is insufficient in terms of thermal comfort, it is considered the sufficient number of subjects to propose and validate a new methodology. The predicted results for all eight activities were significantly. (RMSE: 0.26, CV: 13%). Further, METs were analyzed according to the gender and BMI. The results of analysis by gender show that the METs of men were generally higher than those of women. Analysis according to the BMI reveals that when the BMI is higher, the MET is also higher. However, with respect to sitting and eating food, when the BMI is higher, the MET is lower. Thus, this study suggests a creative method for predicting MET in an indoor environment with a fairly high accuracy. In addition, the difference in MET by behavior was analyzed according to gender and BMI; the results of this analysis is expected to be used as a guideline for more accurate thermal comfort control.

Results: Analysis by gender: In general, MET was higher than female MET. Analysis by BMI: Generally, the higher the BMI, the higher the MET. However, when it comes to sitting and eating activities, the higher the BMI, the lower the MET. As a result, this study proposes a creative method to predict metabolic rates in indoors with a fairly high accuracy. In addition, differences in MET due to behavior were analyzed according to gender and BMI; these results will be used as the basic data for development of more accurate thermal comfort control.

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