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Metabolic Predictive Model for PMV Control Based on Deep Learning

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Abstract**—**In this study, a predictive model for estimating the metabolism (MET) of human body was developed for the optimal control of indoor thermal environment. Human body images for indoor activities and human body joint coordinated values were collected as data sets, which are used in predictive model. A deep learning algorithm was used in an initial model, and its number of hidden layers and hidden neurons were optimized. Lastly, the model prediction performance was analyzed after the model being trained through collected data. In conclusion, the possibility of MET prediction was confirmed, and the direction of the future study was proposed as developing various data and the predictive model.

Keywords**—**Deep learning, indoor quality, metabolism, predictive model.

I. Introduction

As the amount of time that residents spend indoors has increased up to greater than 90% of the day, the importance of maintaining comfortable indoor environmental quality has been emphasized. In particular the thermal environment quality, which is one of the important factors that determines the indoor environment quality, is closely related to not only the improvements on the comfort of residents, but also the building's energy performance. To quantify the indoor thermal environment control, the predicted mean vote (PMV) proposed by Fanger has been adopted. PMV is influenced by occupational MET and clothe (CLO) as well as physical environment factors such as temperature, humidity, air velocity and mean radiant temperature (MRT) [1]. However, few considerations have been paid to the MET, which is unique to each residents, resulting in difficulties in achieving the optimum control of the thermal environment. To overcome this limitation, various studies have been conducted previously, but the application to real buildings has been limited due to the complexity of the measurement method. Thus, this study aimed to predict MET values accurately through the use of an artificial intelligence technique that can produce intelligent predictions for simple applications and objective resident-tailored indoor thermal environment control. To do this, the initial model of MET prediction by indoor activities was developed through a deep learning algorithm and the performance evaluation of the algorithm was conducted.

This study is a foundational stage to develop a model to predict MET values. Its scope was limited to identify the MET value of a single resident. The indoor activities used as training data were selected based on Table I from Metabolic Rates *for Typical Tasks* of ASHRAE 55 to develop the MET predictive model [2]. Utilizing the images corresponding to each of the indoor activities as input data, the prediction performances of the MET were compared and analyzed through using the deep learning algorithm.

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II. Theoretical Discussion

A. Machine Learning

In machine learning, rules are learned by the machine itself from training data, and new data are analyzed by the rules and determination and predictions are performed [3]. Machine learning consists of classification, prediction and grouping algorithms. Depending on whether there is labeled information provided or not, machine learning can be further divided into supervised and unsupervised learning. Supervised learning is a learning method in which the developer informs the answer in advance. On the other hand, the unsupervised learning is a method of self-learning without the process of informing the answer. In addition, there is a reinforced learning which includes the process of collecting training data on its own. In this study, the predictive model used the supervised learning method which informs the answer data. Recently, Machine Learning has been utilized for recognition of spam mail and text, and autonomous driving vehicles [4].

B. Artificial Neural Network and Deep Learning

An artificial neural network (ANN) is an algorithm made by early machine learning researchers. It can process complex operations as it implements the neural system and learning structure similar to the human brain. The basic structure of ANN consists of three layers, these being: input, hidden, and output, which is shown in Fig. 1. A neuron in an ANN plays the role of a transition function which applies a weight to each of the input values to calculate an optimal value.

Deep learning is a form of an advanced ANN, which is also known as a deep neural network (DNN) which consists of two or more hidden layers as shown in Fig. 2. It is a method to increase the training accuracy by increasing the number of nodes and layers as problems become complex.

In architectural field, it is a trend to employ the deep learning to solve the difficulties of inefficient and unpredictable process and systematization [5]. Deep learning is successfully used in the recognition field such as autonomous driving and has good performance in image recognition. Therefore, DNN is suitable as a predictive model in this study for predicting activity by training image of human body. This study implemented a model consisting of fixed hundred hidden neurons for training while changing the hidden layers.

TABLE I
METABOLIC RATES FOR TYPICAL TASKS IN ASHRAE STANDARD 55

Activity	MET Units	Activity	MET Units
Resting		**Miscellaneous Occupational Activities**	
Sleeping	0.7	Cooking	1.6 - 2.0
Reclining	0.8	House cleaning	2.0 - 3.4
Seated, quiet	1.0	Seated, heavy limb movement	2.2
Standing, relaxed	1.2	Machine work	
Walking (on level surface)		Sawing (table saw)	1.8
0.9 m/s, 3.2 km/h, 2.0 mph	2.0	Light (electrical industry)	2.0 - 2.4
1.2 m/s, 4.3 km/h, 2.7 mph	2.6	Heavy	4.0
1.8 m/s, 6.8 km/h, 4.2 mph	3.8	Handling 50 kg (100 lb) bags	4.0
		Pick and shovel work	4.0 - 4.8
Office Activities		**Miscellaneous Leisure Activities**	
Reading.seated	1.0	Dancing, social	2.4 - 4.4
Writing	1.0	Calisthenics/exercise	3.0 - 4.0
Typing	1.1	Tennis, single	3.6 - 4.0
Filling, seated	1.2	Basketball	5.0 - 7.6
Filling, standing	1.4	Wrestling, competitive	7.0 - 8.7
Walking about	1.7	**Driving/Flying**	
Lifting/packing	2.1	Automobile	1.0 - 2.0
		Aircraft, routine	1.2
		Aircraft, combat	2.4
		Heavy vehicle	3.2

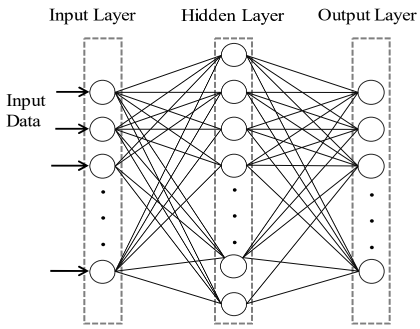

Fig. 1 Structure of Artificial Neural Network

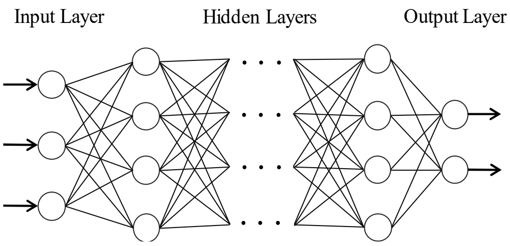

Fig. 2 Deep Neural Network

III. DEVELOPMENT OF HUMAN MET PREDICTIVE MODEL

A. Input Data

The image dataset was obtained from Leeds Sport Pose (LSP) and Frames Falbeled In Cinema (FLIC) to train the predictive model. Images of 16 activities which were considered as indoor activities, that are based on the American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) standards were collected as presented in Table II, and 60 scenes for each indoor activity were prepared (a total of 960 images) [2]. The dataset was configured to have 11 labels in total, based on MET values and each MET value has its label number.

TABLE II
MET DATA FROM ASHRAE ACTIVITY

Activity	Number of Data	MET	Label
sleeping	60	0.7	0
reclining	60	0.8	1
writing reading.seated seated.quiet	180	1.0	2
typing	60	1.1	3
standling.relaxed filling.seated	120	1.2	4
filling.stand	60	1.4	5
cooking	60	1.6	6
walking about	60	1.7	7
machine work.sawing	60	1.8	8
house cleaning machine work.light	120	2.0	9
lifting.packing-lifting lifting.packing-packing	120	2.1	10
Total Number of Data	960		

The input data consisted of human joint coordinate values in the indoor activity images. The number of total joints was 14, which were set to correspond to the major positions which consisted of the legs, arms, neck, and face. The area and location of the coordinates are presented in Table III. The joint areas that cannot be seen in the images were adjusted to (-1, -1).

After these steps, the input data were divided into two cases for the diversity of the input data. That is, the data used in the predictive model consist of two types as shown in Table IV.

Case 1 data consist of MET values and the 14 coordinate values of 960 images. In order to increase training data, Case 2 data was added as input data increased to 1920 through the augmentation step of reversing the coordinates as right side to left side and vice versa.

TABLE III
COORDINATION OF HUMAN JOINTS

Label	Human Body	Joint	Image Example
1		Right Ankle	
2		Right Knee	
3	Leg	Right Hip	
4		Left Hip	
5		Left Knee	
6		Left Ankle	
7		Right Wrist	
8		Right Elbow	
9	Trunk	Right Shoulder	
10		Left Shoulder	
11		Left Elbow	
12		Left Wrist	
13	Head	Neck	
14		Forehead	

TABLE IV
DATA CASE USED IN THE PREDICTIVE MODEL

Type	Images	MET	Augmentation
Case 1	960	11	-
Case 2	1920	11	Reversing the coordinates

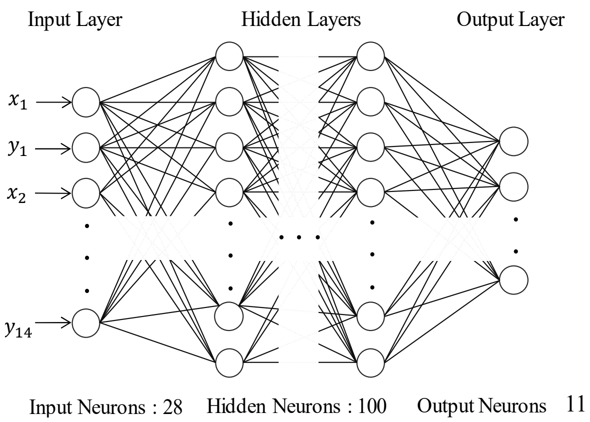

Fig. 3 Structure of Predictive Model

B. Development of Early Model

The classification predictive model was implemented to classify indoor activities with the MET value using the deep learning algorithm. The input data in the predictive model had 28 input values for each image, consisting of the human joint coordinate (x, y) values. Output is the label which is one of the 11 MET values in Table II using the 16 activities coordinate values as the input data.

The predictive model was optimized to improve the prediction rate of correct answers, while controlling the number of hidden layers and the rate of dropout. The optimization was achieved through changing two to three hidden layers with the number of neurons 100 and the dropout rate to 50%, 30% or 0%. Fig. 3 shows structure of the predictive models, which has 28 inputs, 11 outputs and 100 hidden neurons. As an optimizer, adadelta optimizer was used for increasing training speed as considering the learning rate which used to be selected manually to the other optimizer [6].

C. Analysis on Model's Performance

The performance of indoor activity classification in the model was analyzed based on correct answer accuracy rate. This study employed the training using two cases of data in Table IV. Training was conducted for 50,000 times while fixing the number of neurons to 100 and increasing the number of hidden layers from two to three with the dropout rate 50%, 30%, or 0%.

First, the training results of Case 1 which consists of 960 base data are as follows. Since, a large number of nodes and labels in the output, the dropout proceeds in three ways: 50%, 30%, and 0%. Fig. 4 shows the changes of the error rate in relation to five training models of training 960 data. The error was measured every 100 training times, and a total of 50,000 training results are shown. The convergence rate of error is determined by the dropout rate and it converges rapidly to 0 when the dropout is 0%. Therefore, it can be seen that the error rate converges as the input data trained. After training, performance evaluation was carried out through the accuracy of predicting activity using case 1 data. In the Case 1 data, Table V showed that the models 2, 3, and 5 have 100% train accuracy which is the best accuracy rate among the trained models.

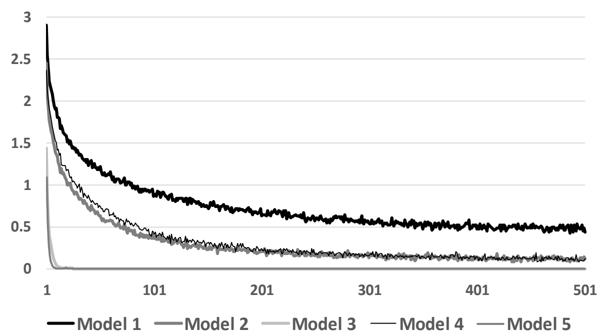

Fig. 4 Error Rate of Case 1 for Training

The results of the Case 2 which consists of 1920 data are shown in Fig. 5 and Table VI. The training times is the same as 50,000 and the change in train accuracy was determined with the doubled data. In Fig. 5, the error converged near zero as training progressed as well and Model 3 and 5 converged to zero fastest with 0% dropout. Table VI shows the performance evaluation results of the model that trained Case 2 data. Unlike Case 1, Model 2 could not satisfy the train accuracy of 100%. However, Models 3 and 5 which are with 0% of dropout have the 100% train accuracy. As a result, the predictive model can be believed that it is trained well about the train data.

TABLE V
TRAIN ACCURACY OF CASE 1 TRAINED MODEL

Model	Hidden Layer	Hidden Neuron	Dropout	Train Accuracy (%)
1	2	100	50%	96.29
2	2	100	30%	100.00
3	2	100	0%	100.00
4	3	100	30%	99.76
5	3	100	0%	100.00

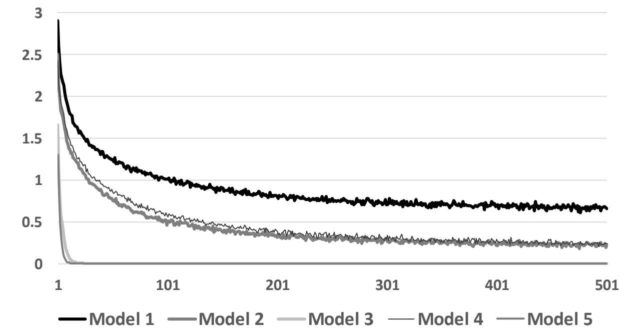

Fig. 5 Error Rate of Case 2 for Training

TABLE VI
TRAIN ACCURACY OF CASE 2 TRAINED MODEL

Model	Hidden Layer	Hidden Neuron	Dropout	Train Accuracy (%)
1	2	100	50%	78.76
2	2	100	30%	94.15
3	2	100	0%	100.00
4	3	100	30%	93.92
5	3	100	0%	100.00

IV. CONCLUSION

This study conducted performance evaluations on the initial model that predicted MET values of residents for indoor thermal environment control. It constructed 960 indoor activity data records for training and preprocessed 1,920 data records that were trained using the deep learning algorithm. The input data were generated with the human body coordinates in the image to be used for training. Training was conducted by changing the structure of the predictive model with two data types. A total of 50,000 trials were trained, and five models were performed. The results are as follows.

1) When the data (Case 1, 2) are training for 50,000 trials, the error converges to zero. This proves that the predictive model about the data is training while reducing errors.
2) The smaller the dropout, the faster the error converges to zero.
3) Both Cases 1 and 2 satisfy train accuracy up to 100%. When the data were increased to Case 2 to vary the input data, the train accuracy is slightly lower than Case 1.

This study was meaningful because it verified training of body joint coordinates through deep learning which was successful, and the MET values were predictable.

Based on these results, the performance of the developed predictive model with the new data will be analyzed and the limitation of the analyzed model can be figured out. It is expected that the accuracy of MET prediction can be improved by optimizing to increase the hidden layer of predictive model more than 4, and increase the number of hidden neurons for advancing the accuracy of MET prediction.

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