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Recognition of Occupants' Cold Discomfort-Related Actions for Energy-Efficient Buildings

Kwonsik Song[1], Kyubyung Kang[2]*, Byung-Cheol Min[3]

[1] *School of Construction Management Technology, Purdue University, 401 N.Grant St. West Lafayette, IN 47907, USA,* E-mail address: song736@purdue.edu
[2] *School of Construction Management Technology, Purdue University, 401 N.Grant St. West Lafayette, IN 47907, USA,* E-mail address: kyukang@purdue.edu
[3] *Department of Computer and Information Technology, Purdue University, 401 N.Grant St. West Lafayette, IN 47907, USA,* E-mail address: minb@purdue.edu

Abstract: HVAC systems play a critical role in reducing energy consumption in buildings. Integrating occupants' thermal comfort evaluation into HVAC control strategies is believed to reduce building energy consumption while minimizing their thermal discomfort. Advanced technologies, such as visual sensors and deep learning, enable the recognition of occupants' discomfort-related actions, thus making it possible to estimate their thermal discomfort. Unfortunately, it remains unclear how accurate a deep learning-based classifier is to recognize occupants' discomfort-related actions in a working environment. Therefore, this research evaluates the classification performance of occupants' discomfort-related actions while sitting at a computer desk. To achieve this objective, this study collected RGB video data on nine college students' cold discomfort-related actions and then trained a deep learning-based classifier using the collected data. The classification results are threefold. First, the trained classifier has an average accuracy of 93.9% for classifying six cold discomfort-related actions. Second, each discomfort-related action is recognized with more than 85% accuracy. Third, classification errors are mostly observed among similar discomfort-related actions. These results indicate that using human action data will enable facility managers to estimate occupants' thermal discomfort and, in turn, adjust the operational settings of HVAC systems to improve the energy efficiency of buildings in conjunction with their thermal comfort levels.

Keywords: Energy Efficiency, Thermal Comfort, Vision Sensor, Deep Learning, Action Recognition

1. INTRODUCTION

Buildings consume approximately 40% of total energy in the U.S. [1]. Consequently, much effort has been devoted to reducing energy consumption in the building sector through technical (e.g., thermal insulation improvement [2,3]) and operational (e.g., control strategies for mechanical and electrical equipment [4,5]) solutions. Particularly, energy-efficient operation of heating, ventilation, and air conditioning (HVAC) systems has received significant attention because they account for about 50% of total energy consumption in buildings [4,6].

HVAC control strategies should involve evaluating the thermal comfort level of occupants because it significantly affects their work productivity [7]. This becomes more significant for the following two reasons. First, individuals' work mainly takes place in buildings (e.g., offices and labs). Second, the thermal comfort level of occupants changes over time due to their interaction with personal (e.g., metabolic rate) and environmental (e.g., air temperature) factors. Traditionally, the Predicted Mean Vote (PMV) model, which considers the personal and occupational-environmental factors, has been widely used to evaluate how occupants feel in certain situations [8]. Recently, several researchers investigated occupants' physiological signals (e.g., heart or electrodermal activity) using wearable biosensors (e.g., wristband) to estimate their feelings in given thermal environments [9–11]. However, these evaluation methods require occupants to collect their personal data (e.g., survey on clothing) or the devices for all occupants. Thus, it is financially infeasible to evaluate the thermal comfort level of occupants in buildings.

The advanced technologies in sensing and computation provide new opportunities to overcome some of these limitations. With vision sensors, it is possible to collect video data on which actions occupants take in the indoor environment. Considering that individuals exhibit specific actions (e.g., rolling up shirt sleeves) when they feel thermal discomfort, the vision sensors enable the detection of such actions in a non-invasive and scalable manner. Moreover, integrating vision sensors with deep learning (DL) enables the real-time recognition of occupants' discomfort-related actions in buildings. Unfortunately, despite the potential benefit of using human action data, less attention has been given to evaluating the classification performance of occupants' discomfort-related actions while sitting at a computer desk. This is important because human action recognition can vary depending on surrounding environments (e.g., computer monitors hiding human actions). To date, several DL-based classifiers [12] have been trained and tested using human action data to classify occupants' discomfort-related actions. However, there are still limitations because the data for training and testing classifiers was collected from human subjects who took several discomfort-related actions while standing. Thus, it still remains unclear how accurate a DL-based classifier is in recognizing occupants' thermal discomfort while sitting at a computer desk.

To fill the gap in the literature, this research evaluates the classification performance of occupants' discomfort-related actions in working environments to see the feasibility of human action data for thermal comfort evaluation. To achieve this objective, a DL-based classifier is trained and tested using RGB video data from human subjects who take cold discomfort-related actions while sitting at a computer desk. The trained classifier could enable the real-time estimation of occupants' thermal discomfort, thus making it possible to adjust the operational settings of HVAC systems to create energy-efficient and comfortable environments in buildings.

2. RECOGNITION OF OCCUPANTS' COLD DISCOMFORT-RELATED ACTIONS

To recognize occupants' discomfort-related actions in working environments, a DL-based classifier is trained using human action data in the following four steps (Fig. 1): 1) data annotation, 2) human pose estimation, 3) classifier training, and 4) thermal comfort evaluation.

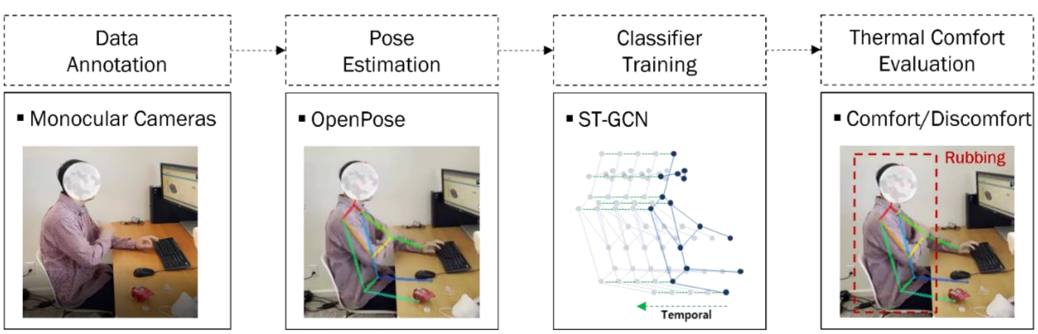

Figure 1. Recognition process of occupants' discomfort-related actions in working environments

2.1. Data Annotation

Once RGB video data is collected using single or multiple monocular cameras, it is manually labeled depending on which discomfort-related actions occupants did.

2.2. Pose Estimation

A set of human body joints is extracted from each frame of the labeled RGB videos to generate occupants' skeletons. A skeleton-based representation of human actions is more robust to the variations of illumination, camera viewpoints, and background changes than an RGB-based representation [13]. An OpenPose toolbox [14] is readily available from online sources to extract human body joints from RGB video data. This toolbox provides users with information about where 18 body joints are located in the form of 2D coordinates. Thus, based on 2D coordinates of human body joints, it is possible to represent a sequence of occupants' skeletons.

2.3. Model Training

A Spatial-Temporal Graph Convolutional Network (ST-GCN) is adopted for the classifier training to classify occupants' discomfort-related actions using the recognized skeletons. It can learn about how human skeletons behave over time [15]. Also, since human skeletons are in the form of graphs instead of 2D or 3D grids, the ST-GCN is more suitable for skeleton-based human action recognition than other classifiers (e.g., recurrent neural network or convolutional neural network). An ST-GCN model is trained using the labeled skeleton data in the following three steps. First, a spatial-temporal graph is constructed with human body joints as graph nodes to form a hierarchical representation of the skeletons' sequence. Second, the joint coordinate vectors on the graph nodes are used as an input of ST-GCN, and the vectors generate higher-level feature maps on the graph. Third, a standard SoftMax classifier classifies the graph to the corresponding category of discomfort-related actions. During the model training, a backpropagation algorithm updates connection weights between nodes in two adjacent layers to improve the classification accuracy of occupants' discomfort-related actions.

2.4. Thermal Comfort Evaluation

The newly collected RGB video data on occupants' actions are used as input data for the trained classifier to estimate their thermal discomfort. If occupants' actions are classified into one of the predetermined discomfort-related actions, they are considered as being thermal discomfort in given environments. Otherwise, the trained classifier indicates that occupants feel thermally comfortable in given environments.

3. DATA COLLECTION AND ANNOTATION

To evaluate the classification performance of occupants' discomfort-related actions in working environments, RGB video data was collected from nine college students. All the participants were asked to sit at a computer desk and take six cold discomfort-related actions five times (Figs. 2-a and 2-b). In the extensive literature [12,16–18], these actions have been widely regarded as individuals' behavioral responses to cold ambient conditions. To record these actions, four monocular cameras were set at the same height of 1.8m but different angles (i.e., 0°, 45°, 90°, and 135°) (Fig. 2-c). After that, they turned around to the opposite side and took the same actions five more times. This means that a cold discomfort-related action by each participant was recorded at eight different camera angles.

Each video clip shows one cold discomfort-related action, which one participant took for 3-10 seconds. However, video clips from camera angles of 0° and 180° were excluded from the analysis because they provided insufficient information about participants' actions (i.e., hidden by computer

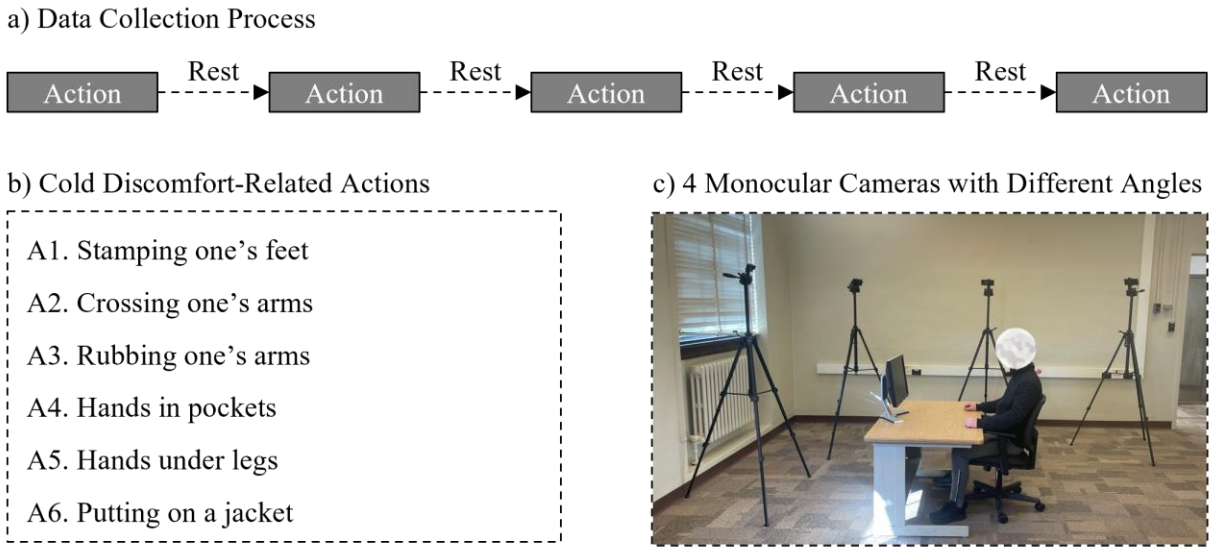

Figure 2. Data collection process.

monitors and their backs), thus limiting the extraction of their skeletons. In total, 3,384 video clips were included in the analysis.

4. RESULTS AND DISCUSSIONS

A classifier was trained and tested using the collected video clips to evaluate the classification performance of occupants' discomfort-related actions in working environments. The video clips were randomly divided between training and testing with a 70/30 split. The classification results were mainly evaluated using classification accuracy (Eq. 1).

$$Accuracy = \frac{1}{total\ observations}\sum_{i=1}^{k} t \cdot p_i \tag{1}$$

where, $t \cdot p_i$: the number of correctly identified observations for action i. Classification accuracy is the primary measure of classification performance.

The classifier has an average accuracy of 93.9% for classifying occupants' cold discomfort-related actions while sitting at a computer desk (Table 1). When investigating the classification accuracy by the type of cold discomfort-related actions, the trained model achieves 100% accuracy for A1 (stepping on one's feet) and A6 (putting on a jacket). Other actions are recognized with a classification accuracy of 86.9% for A2 (crossing one's arms), 95.0% for A3 (rubbing one's arms), 89.7% for A4 (hands in pockets), and 94.6% for A5 (hands under legs). These results indicate a high level of accuracy for classifying occupants' cold discomfort-related actions. Compared to the classification results by previous researchers [12], it can be seen that the trained classifier provides comparable classification performance despite its view-limited setting of data collection (i.e., hidden by a computer desk and monitor) (Table 1). This can be explained by the fact that the classifier was trained using the video data from multiple cameras with different angles.

Additionally, classification errors are mostly observed between A2 (folding arms) and A3 (rubbing arms) and between A4 (hands in pockets) and A5 (hands under legs) (Fig. 3). These errors can be understandable because human body joints representing the discomfort-related actions share similar locations (e.g., crossing arms vs. rubbing arms). Considering that individuals' discomfort-related actions indicate different levels of thermal comfort (e.g., cold, cool, or slightly cool) [12], it is necessary to distinguish these similar actions. One way to avoid such errors would be to train multiple classifiers using data from different angles of cameras (e.g., four individually trained classifiers using data from four different angles of cameras) because cameras can have different levels of information about human actions depending on where they are located. Thus, by choosing a classifier with a high possibility, it could be possible to distinguish similar discomfort-related actions.

Table 1. Classification Accuracy of Occupants' Cold Discomfort-Related Actions

Data Collection Setting	Cold Discomfort-Related Action						
	Overall	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**
Sitting at a desk	93.9%	100%	86.9%	95.0%	89.7%	94.6%	100%
Standing [12]	-	85.4%	93.7%	-	-	-	97.8%

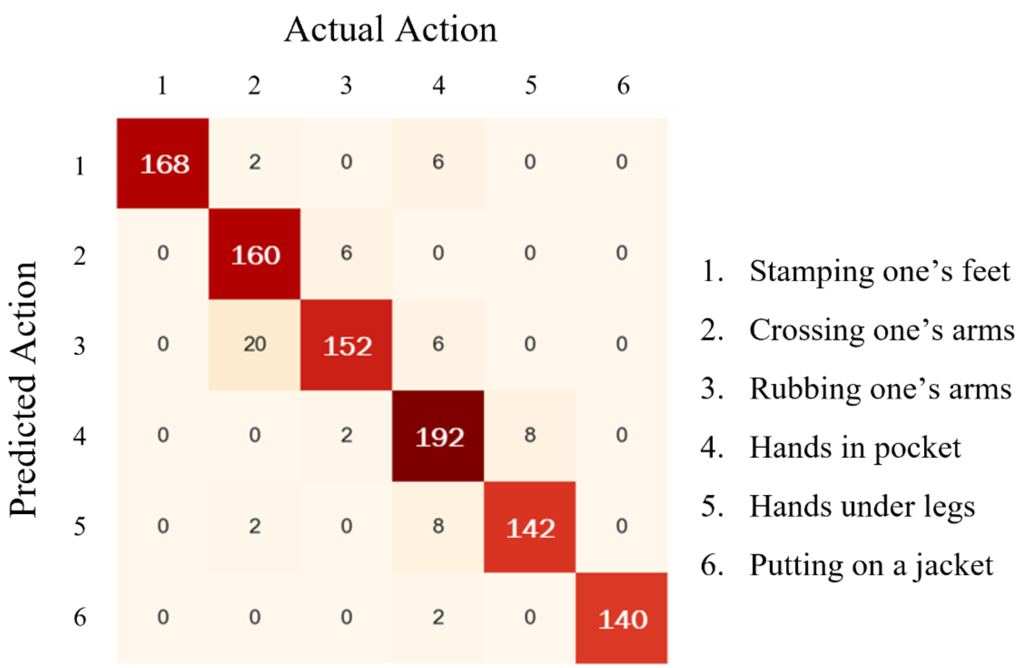

Figure 3. Confusion matrix of actual and predicted cold discomfort-related actions

The classification results support that the trained classifier can be adopted as an operational solution to estimate occupants' thermal discomfort in buildings. By including the estimation results in the HVAC control process, it could be possible to create more comfortable environments in buildings with less energy consumption. However, two issues might arise about extending its practical application. First, occupants' warm discomfort-related actions (e.g., fanning or rolling up sleeves) need to be involved in the model training process. They exhibit the actions during summer months and even during winter months due to overheating by HVAC systems. Thus, it is necessary to train and test a classifier using video data about occupants' warm discomfort-related actions. Second, building occupants may take several common actions similar to discomfort-related actions (e.g., putting on jackets to leave office rooms or remove them). To overcome this issue, a classifier should consider the occurrence time of actions alongside environmental characteristics (e.g., indoor temperature and humidity) during its training process.

5. CONCLUSIONS

This study evaluated the classification performance of occupants' cold discomfort-related actions in working environments. We extracted 2D human skeletons from RGB videos and trained a classifier using the skeleton data to classify occupants' cold discomfort-related actions. The classification results showed that the trained model classifies occupants' cold discomfort-related actions with an average accuracy of 93.9%. Also, relatively low classification accuracy was found among similar discomfort-related actions.

This research contributes to the literature by demonstrating the feasibility of using human action data to classify occupants' discomfort-related actions while sitting at a computer desk. This will enable facility managers to estimate occupants' thermal discomfort and, in turn, adjust the operational settings of HVAC systems to create a more thermally comfortable while improving the energy efficiency. Future research will train and test a classifier of occupants' warm discomfort-related actions in conjunction with data on their occurrence time and environmental characteristics (e.g., indoor temperature and humidity).

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