Human-Centered Behavioral Analysis of Window Operation Using AI-Based Skeletal Recognition

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***Abstract*—This study presents a quantitative approach to analyzing window opening and closing behaviors using skeletal recognition technology. Video data of five participants performing these actions were captured and processed using the Openpose model, which detects 25 human joints. Focusing on the shoulder, elbow, and wrist, the study analyzed time-series joint coordinates to identify motion patterns and behavioral characteristics. The results revealed consistent relationships among joint movements and enabled accurate distinction between left- and right-hand operations. In addition, behavioral distribution characteristics were examined by visualizing horizontal and vertical skeletal displacements. The results showed that stationary postures are concentrated near a reference origin, whereas window operation actions produce distinct spatial shifts in the coordinate space, indicating that occupant behavior can be interpreted as a sequence of state transitions composed of distinct behavioral phases. The findings confirm that skeletal data can effectively represent occupant behavior without intrusive sensors, providing a non-contact and privacy-preserving monitoring method. This approach contributes to the development of human-centered intelligent building systems that can adapt indoor environments in real time based on occupant actions, thereby improving both thermal comfort and energy efficiency. Future research will expand behavioral categories and explore real-time implementation in smart building applications.**

Keywords*—Image processing; skeletal recognition; behavioral analysis; Openpose

I. Introduction

In recent years, the rapid advancement of digital technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) has significantly influenced the architecture and construction industries. These emerging technologies have enabled the development of intelligent, responsive environments that can adapt to human behaviors and preferences in real time [1]. Buildings are no longer static structures; they are evolving into dynamic systems capable of sensing, interpreting, and responding to occupants' needs. Among the many applications of IoT and AI in architecture, the creation of human-centered thermal environments has become an area of growing research interest [2].

Traditional environmental control systems, such as heating, ventilation, and air conditioning (HVAC), rely primarily on temperature, humidity, and occupancy sensors to regulate indoor conditions. However, such systems often neglect the diversity and variability of human behavior, which plays a critical role in determining comfort levels. For instance, an occupant's decision to open or close a window can significantly affect indoor temperature, air quality, and energy consumption. Understanding and predicting these behavioral patterns are essential for designing energy-efficient buildings that maintain comfort without excessive energy use [3, 4].

Recent studies have demonstrated that IoT-based monitoring systems can capture and analyze occupant behavior with high temporal and spatial resolution. By connecting sensors, cameras, and data analytics platforms, researchers can model the relationship between human actions and environmental parameters [5]. At the same time, AI technologies, including machine learning and computer vision, have made it possible to interpret complex human motions automatically. For example, deep learning-based image recognition models can detect gestures, postures, and movements that correspond to specific behaviors such as window operation, light switching, or adjusting clothing layers [6, 7].

Despite these advancements, challenges remain in achieving reliable and context-aware recognition of occupant behaviors. Many existing studies rely on wearable sensors or environmental data, which may not fully capture the physical actions associated with comfort regulation. Moreover, privacy concerns often limit the use of conventional video data in indoor monitoring applications [8]. To address these challenges, recent research has explored the use of skeletal recognition and pose estimation techniques, which analyze the positions of human joints rather than identifiable facial features. Such approaches provide a balance between behavioral accuracy and privacy protection [9, 10].

In this context, the present study investigates window-opening and closing as a form of architectural and environmental behavior using skeletal recognition technology. Rather than treating window operation as a simple motion detection task, this study interprets it as an occupant-driven behavioral process that influences indoor thermal conditions and energy performance. By capturing and modeling these behaviors, the research aims to support the development of intelligent, privacy-preserving, and human-centered building control strategies.

II. Literature Review

Many researchers have used the Internet of Things (IoT) and artificial intelligence (AI) technologies to study various issues in the architectural field. In recent years, research on human-centered thermal environments has attracted considerable attention [11, 12].

Henning Metzmacher et al. [13], Bin Yang et al. [14], and Yeyu Wu et al. [15] used thermal imaging camera images and skin sensors to analyze the thermal sensation of occupants in real-time and to control the indoor thermal environment according to the number of occupants. Mateus Vinícius Bavaresco et al. [16] and Muhammad Aftab et al. [17] monitored IoT-based buildings to provide an optimal thermal environment for behavioral changes of occupants. Miao Zang et al. [18] investigated human-centered indoor environment control methods based on image data collected using IoT technology.

Wenjun Duan et al. [19] investigated a method for detecting the behavior of changing the amount of clothing in real-time using video data. Kailai Sun et al. [20] used AI technology to classify the standing and sitting positions of occupants and attempted a human flow line analysis.

AI technology has also been used in many other fields to solve a variety of problems. Table I shows previous studies that used AI.

TABLE I SUMMARY OF PREVIOUS STUDIES

Field	Authors	Year	Main contributions
Behavior modification	Tomoya Tamei et al. [21]	2015	AI technology was used to analyze human movement behavior
	Teruhiro Mizumoto et al. [9]	2018	Behavioral pattern analysis of kitchen occupants
	Zhu Bin et al. [5]	2020	Detection and recognition of abnormal pedestrian behavior
Arts	Yan Wang et al. [22]	2023	Algorithm development to detect dance poses using AI technology
	Amir Irfan Mazian et al. [23]	2023	AI technology was used to detect the dance poses
Medical	Thanh-Hai Tran et al. [24]	2017	Development of a behavior detection system for inpatients falling out of bed
	Ramesh Balaji et al. [25]	2018	Development of a health management system for the elderly using AI remote control monitoring
	Nur Khalidah Zakaria et al. [26]	2021	Development of a method for detecting the behavior of people with disabilities
Safety	Manoj Kurien et al. [27]	2017	Development of a safety behavior detection system using 3D model simulation
	Paige Wenbin Tien et al. [4]	2020	Detection of work behavior of occupants in office buildings
	Chengle Fang et al. [28]	2022	Development of a safety action detection system for construction sites
	Zhe Sun et al. [29]	2023	Detection of clothing at construction sites using AI detection systems
	Xiangang Cao et al. [30]	2023	Investigation of a method for detecting safe behavior using skeletal recognition
Education	Guy Gaziv et al. [31]	2017	Development of a conversational behavior support system using 3D models and AI technology
	Soohyun Choi et al. [32]	2020	Development of a child behavior pattern analysis and facial expression recognition system using AI application technology

III. Methodology

A. Experiments Summary

Window opening and closing detection is made more efficient by directly analyzing the behavior of occupants. In addition, quantitative analysis methods must be considered to realize a human-centered built environment. In this study, cameras were installed in the room to collect video data of five occupants opening and closing windows. The camera was set to FPS 30, and the video data were saved on an SD card. The format of the data is *.mp4, 3840(px) × 2160(px) movie. Fig. 1 shows the details of the experimenter. The experimenters were men between 167 and 178 cm in height. All experimenters were right-handed.

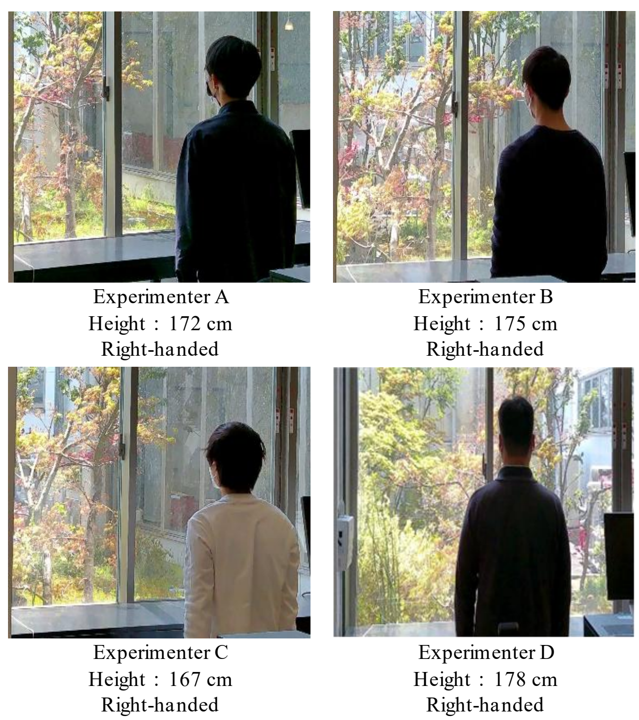


Fig. 1. Experimental information.

B. Window Opening and Closing Behavior

The following procedure was used to detect the window-opening and closing behavior of the experimenter. Fig. 2 shows the experimental setup:

1) Stands in front of a window.
2) The window was opened with the left hand.
3) The window was closed with the left hand.
4) The window was opened with the right hand.
5) The window was closed with the right hand.
6) Stand in front of the window when all the actions are completed.

C. Data Preprocessing

The video data accumulated in the experiment were preprocessed to analyze the window-opening and closing behavior. Data preprocessing was performed by extracting the video data into still images and organizing the window-opening and closing behavior from the position of standing in front of the window. Data preprocessing consisted of the following steps. Fig. 3 shows the data preprocessing flow.

1) The experimental video was edited to the necessary parts using a video-editing program.
2) Still images were extracted using OpenCV.
3) Delete personal information, such as faces.
4) Window opening and closing movements were classified through visual observation.
5) Organizing the data for each researcher.

D. Skeleton Recognition

In this study, skeletal recognition was used to analyze window opening and closing behaviors. Skeletal recognition uses the Openpose model, which detects 25 human joints. Fig. 4 shows the skeletal recognition items and an image diagram of the Openpose model. The results of detecting the experimenter's joints were stored in the JavaScript Object Notation (JSON) format with numerical coordinate data for each joint. Window opening and closing behavior was analyzed using joint coordinate data. In this report, we extracted data on joint numbers 2, 3, and 4 of the right arms, as shown in Fig. 4, and joint numbers 5, 6, and 7 of the left arms for behavioral analysis. Behavioral analysis analyzed window-opening and closing behavior based on the direction in which the left and right arms moved with respect to each joint data standing in front of the window (see Fig. 5).

Fig. 2. Window opening and closing actions.

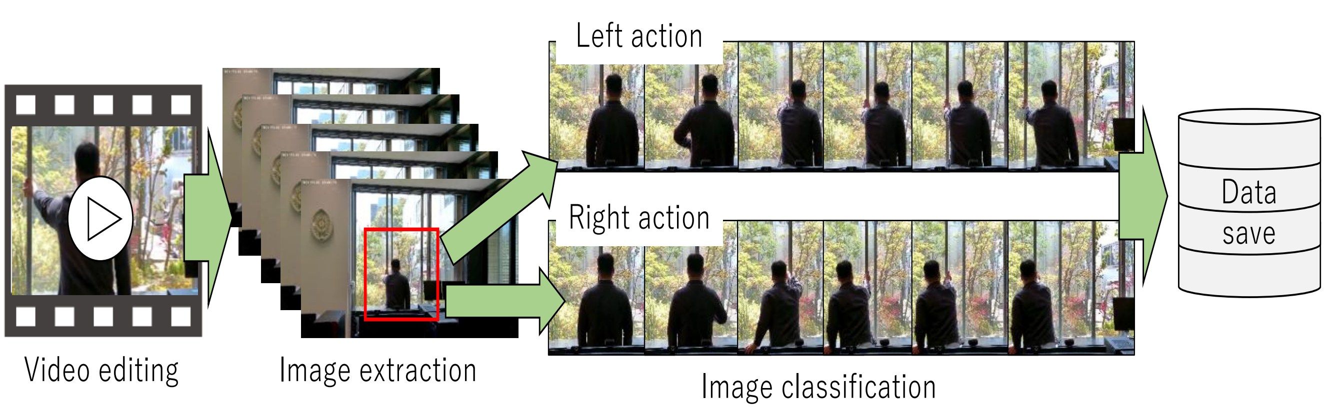
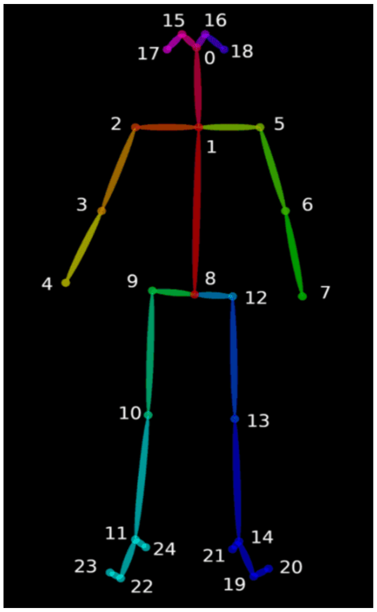
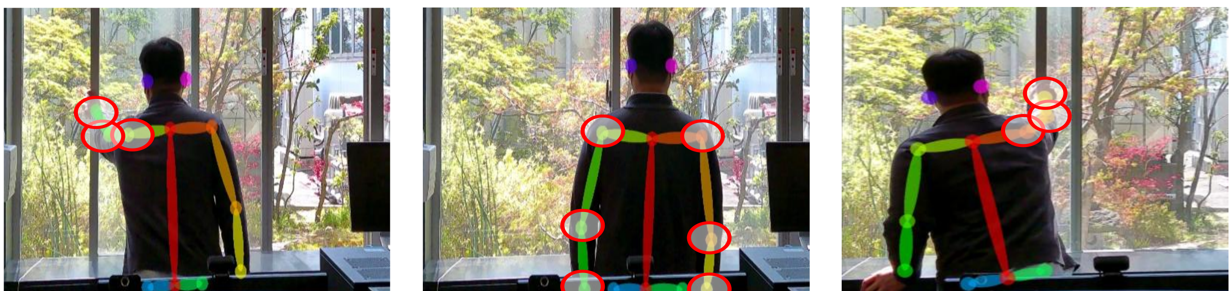


Fig. 3. Data preprocessing flow.



0	Nose	13	LKnee
1	Neck	14	LAnkle
2	RShoulder	15	REye
3	RElbow	16	LEye
4	RWrist	17	REar
5	LShoulder	18	LEar
6	LElbow	19	LBigToe
7	LWrist	20	LSmallToe
8	MidHip	21	LHeel
9	RHip	22	RBigToe
10	RKnee	23	RSmallToe
11	RAnkle	24	RHeel
12	LHip	25	Background

Fig. 4. Openpose model.



Left opening and closing Standing Right opening and closing

Fig. 5. Pattern setting of behavior and skeletal location of features.

IV. RESULTS

A. Behavioral Analysis of Window Opening and Closing Actions

The analysis of window opening and closing behavior was conducted based on skeletal coordinate data, using six predefined behavioral patterns (see Fig. 6). The analysis focused on the subject's posture when standing in front of the window, utilizing the coordinate data of the left and right shoulders, elbows, and wrists. Each set of skeletal coordinates was represented as a time series, and variations in these coordinates were analyzed. Fig. 6 illustrates the window opening and closing behavior. The figure shows the temporal changes in the joint positions of the subject's upper limbs for both the left and right arms. The left column visualizes the detected joint points (Shoulder, Elbow, Wrist) obtained from the pose estimation algorithm, while the right column plots the frame-by-frame changes of each joint point along the orthogonal (vertical) coordinate axis.

During the sequence of actions from preparatory motion to actual window operation, both the x- and y-coordinates changed over time. The magnitude of these variations also differed depending on the degree of window opening or closing. While the y-coordinates tended to converge along a similar line during the motion, the x-coordinates of the shoulder, elbow, and wrist showed distinct changes.

From the graphs, it was observed that in all movements, the coordinate values followed the order Shoulder → Elbow → Wrist, decreasing as the joints moved downward. After the onset of movement, the coordinate values for each joint rapidly decreased between approximately frames 1 and 5, and then remained nearly constant. This indicates that during the arm-raising motion, the wrist and elbow descended and reached a stable posture.

A comparison between the left and right arm movements revealed similar coordinate change patterns, though the magnitude of change for the right arm was slightly smaller. This suggests that the right arm had a more limited range of motion, possibly due to the camera angle or the subject's dominant hand. Furthermore, a clear transition from "Left" to "Right" motion was observed around frame 7, accompanied by significant coordinate changes during the transition from the standard posture to each motion segment. This confirms that the system was able to accurately distinguish between left and right movements.

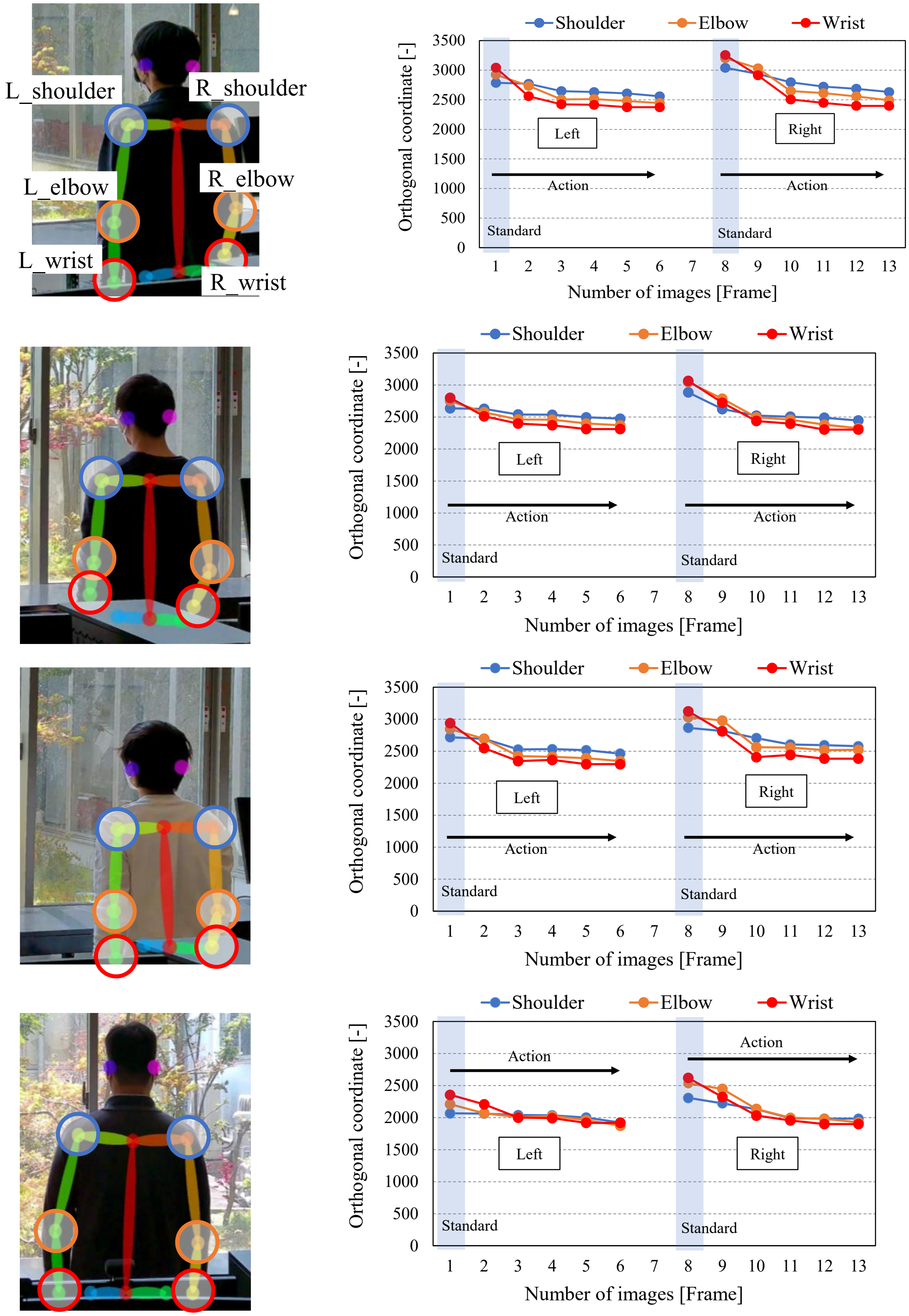


Fig. 6. Left and right coordinate analysis.

The results demonstrate that the proposed pose estimation model can reliably track changes in the positions of upper-limb joints (shoulder, elbow, wrist) across consecutive frames. Meanwhile, the relatively large variations observed in the elbow and wrist coordinates can be attributed to their roles as the primary movable joints of the upper limbs, which are strongly influenced by motion.

Additionally, since the coordinate variation patterns were similar between left and right movements, the model is considered to maintain consistent estimation performance for symmetrical actions.

B. Behavioral Distribution Characteristic

Fig. 7 presents a visualization of the horizontal and vertical behavioral displacements of five subjects standing in front of a window, expressed using skeletal coordinate data. A reference posture corresponding to a stationary standing position is defined near the origin, enabling variations in behavior and transition processes to be represented within a two-dimensional coordinate space.

The results show that when subjects remain stationary in front of the window, the skeletal coordinates are concentrated near the origin, generally within approximately 1000 units along the x-axis and 600 units along the y-axis. In contrast, during the action of fully opening the window, the skeletal coordinates exhibit a pronounced shift toward the right and upward directions. This pattern reflects the combined effects of lateral body movement and upward motion of the arms and upper body associated with window operation.

Although window opening and closing actions are continuous in nature, the corresponding skeletal coordinate distributions are separated into multiple regions within the feature space. This indicates that the behavior can be more appropriately interpreted as a sequence of state transitions comprising distinct behavioral phases, rather than as a single static state. Furthermore, the observed distributions suggest that occupant behavior does not evolve linearly along a single trajectory but transitions between different states through multiple pathways. The identification of several spatially distinct subregions provides additional insight into behavioral characteristics that are not fully captured by conventional simplified stage-based models.

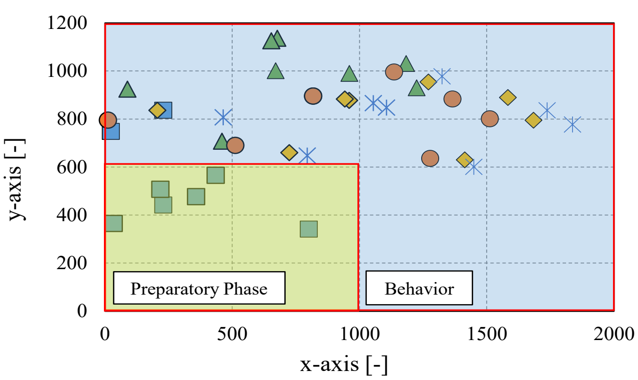


Fig. 7. Horizontal and vertical behavioral displacements in skeletal coordinate space.

V. Conclusion

This study proposed a quantitative approach for analyzing window-opening and closing behavior using skeletal recognition technology. By employing the Openpose model, the movements of upper-limb joints (shoulder, elbow, and wrist) were extracted and analyzed from video data captured during controlled experiments. The results demonstrated that skeletal coordinate data effectively represented the motion patterns of window operation, allowing the system to distinguish between left and right arm movements with high accuracy.

The analysis revealed that coordinate variations followed a consistent pattern across different participants, indicating that the pose estimation model maintained stable recognition performance even for symmetrical actions. Furthermore, the time-series data of joint positions successfully captured the transition of movements from preparation to completion, suggesting that this method can serve as a reliable basis for quantifying occupant behavior.

These findings contribute to the development of human-centered environmental control systems by providing a foundation for integrating behavioral analysis into building automation. The ability to automatically detect occupant actions such as window operation enables real-time adjustment of indoor thermal environments, which can enhance comfort and energy efficiency simultaneously.

Future research should focus on expanding the dataset to include diverse environmental conditions, body postures, and participant demographics. Integrating additional sensory inputs, such as thermal imaging and environmental sensors, may further improve the robustness of behavior recognition and contribute to the realization of adaptive, occupant-responsive smart buildings.

VI. Future Research Works

While this study successfully demonstrated the feasibility of detecting window-opening and closing behaviors using skeletal recognition, several areas remain for further investigation and refinement.

Future studies should expand the experimental environment to include more diverse participants, varied body types, and different window designs or installation heights. Such expansion would enable more robust generalization of the proposed model across real-world conditions.

In addition, future work will focus on incorporating machine-learning classifiers to quantitatively evaluate behavior recognition performance, including accuracy, precision, and recall. Comparative analyses with existing methods will also be conducted to further clarify the effectiveness and limitations of the proposed approach.

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AUTHORS' PROFILE

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