A Framework for Real-Time Estimation of Human Activity Intensity in Indoor Environments

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Abstract

The real-time estimation of human activity level in indoor environments is crucial for thermal comfort prediction and optimizing HVAC systems, as well as supporting health monitoring and ergonomic assessments. Existing methods typically categorize activities into predefined types and therefore are not efficient for new activities. Furthermore, the transition between activities is not captured in these classification methods. To address these limitations, we propose a novel Activity Intensity Score (AIS) framework that provides a continuous, non-intrusive assessment of human activity intensity. The proposed AIS framework uses kinematic parameters derived from video-based pose estimation to calculate a dynamic intensity score. Key kinematic parameters, such as angular speed, angular acceleration, range of motion, movement frequency, and rotational energy, are extracted from pose landmarks using MediaPipe. These parameters are then normalized and combined to generate a continuous AIS that reflects real-time variations in movement intensity. The proposed approach was validated through controlled experiments with participants performing activities of varying intensities, including low (e.g., sitting), moderate (e.g., walking), and high (e.g., jumping jacks). Results showed that the AIS effectively distinguishes between different activity intensities, with higher AIS values corresponding to more intensive activities. The proposed method addresses the need for a more granular understanding of activity levels beyond simple categorical classification. This research contributes to real-time activity estimation, which has applications in optimizing indoor environmental conditions, health monitoring, and dynamic ergonomic assessments.

Keywords – Activity Intensity Score; Real-Time Estimation; Kinematic Chains; Computer Vision

1 Introduction

In indoor environments, the real-time estimation of human activity intensity plays a crucial role in optimizing environmental control systems, such as HVAC, as well as supporting health monitoring and ergonomic assessments [1], [2], [3], [4], [5]. Traditional HVAC systems operate with predefined control settings that do not respond to changes in occupant behavior or environmental conditions [6]. Dynamic HVAC systems that adapt to real-time changes in occupant activities can significantly enhance both comfort and energy efficiency. Therefore, such systems are essential for addressing the dynamic requirements of occupants, since they provide intelligent, responsive adjustments that improve overall indoor conditions. With recent progress in AI-driven models, the autonomous HVAC control systems have been developed to adjust the settings by considering energy efficiency and thermal comfort of occupants. However, typically in these models the role of human activity in thermal comfort is simplified by assuming comfort as a function of environmental parameters such as temperature [7], [8], [9], [10], which often leads to either excessive energy consumption or inadequate thermal comfort for the occupants.

The activity intensity is a key determinant of a building occupant's thermal comfort perception, as it directly influences the body's energy expenditure, similar to how metabolic rate (MET) is used in thermal comfort models like PMV [11]. This energy expenditure impacts the thermal conditions required for maintaining comfort, making activity intensity an essential parameter for dynamic HVAC adjustments. Since dynamic HVAC systems require real-time adjustments to occupant behavior, understanding activity levels is crucial for enabling these systems to respond effectively to varying thermal demands [12], [13]. For example, an individual engaging in physical activity generates more body heat compared to someone resting, requiring different temperature regulation to maintain comfort [14]. By integrating activity intensity information, environmental control systems can achieve a better balance between energy consumption and occupant comfort. Additionally, human activity level estimation can support health monitoring, as sudden changes in activity patterns may indicate health issues that need attention [3], [14].

Although understanding occupant activity intensity is essential for dynamic HVAC adjustments, most existing approaches focus on activity recognition, which involves categorizing activities into distinct types such as walking, sitting, or running [15], [16]. These activity recognition methods face limitations in addressing the needs of adaptive environmental control, as they typically focus on discrete classifications rather than providing a continuous measure of activity intensity [1]. This not only limits their functionality for certain defined activities, but also fails to provide the nuanced understanding required for optimizing HVAC systems. For HVAC control, a more granular understanding of activity intensity is beneficial, as it allows for finer adjustments to the environment in real time. Furthermore, many existing approaches rely on wearable sensors, which present practical limitations due to being intrusive and uncomfortable for users [12], [17], [18], [19]. As a result, there is a need for a non-intrusive, real-time solution that provides a continuous measure of activity intensity, overcoming the limitations of predefined activity categories, and effectively linking activity levels to their impact on energy expenditure and thermal comfort.

To address these challenges, this research proposes a novel Activity Intensity Score (AIS) framework that uses movement data to provide a continuous measure of activity intensity. The AIS framework is designed to overcome the limitations of existing activity recognition methods by providing a detailed and dynamic assessment of activity intensity rather than discrete activity classes. This approach integrates various kinematic parameters, such as angular speed, angular acceleration, range of motion (ROM), and cumulative effort index (CEI), to generate a continuous intensity score that reflects real-time movement variations across different parts of the body. By focusing on these parameters, the AIS framework provides a more detailed and dynamic assessment of activity intensity, which is crucial for optimizing HVAC systems and supporting health monitoring while addressing the need for accuracy and adaptability. Importantly, AIS can be calculated using any image data, including thermal imaging or visible-light cameras, allowing flexibility in its application. The key contributions of this work include the development of a novel AIS framework that estimates human activity intensity based on thermal imaging data. The proposed approach has been validated through real-world experiments, demonstrating its capability to assign a proper score for differentiating various activity levels.

2 Methodology

The proposed activity intensity estimation framework, as depicted in Figure 1, aims to continuously assess the activity intensity of building occupants by analyzing movement data derived from image frames. The framework consists of five phases that together provide a comprehensive approach for estimating activity intensity. First, human body landmarks are detected using pose estimation to create a time series representation of body movements. Next, specific body segments, known as kinematic chains, are selected, and joint angles are computed to analyze movement patterns. Then, key movement parameters such as angular speed, acceleration, and range of motion are extracted and normalized. These normalized parameters are combined to compute the Activity Intensity Score (AIS) for each kinematic chain. Finally, AIS values from all kinematic chains are aggregated to produce an overall measure of activity intensity. Each phase is explained in detail in the following sections.

2.1 Pose Estimation and Landmark Detection

The first phase focuses on extracting accurate human body landmarks from video frames to enable kinematic analysis. This phase uses the MediaPipe Pose, an advanced pose estimation library developed by Google [20]. MediaPipe Pose is a machine learning-based framework that detects and tracks human body landmarks from video frames, providing real-time and high-confidence estimations. MediaPipe utilizes a combination of deep learning and computer vision techniques to effectively identify 33 key human body landmarks, including major joints such as shoulders, elbows, wrists, hips, knees, and ankles.

The pose estimation algorithm processes each video frame and extracts the 3D coordinates (x, y, z) of these relevant body joints. These coordinates are then used to construct a time series representation of the subject's body landmark positions, capturing the dynamic movements over time. The outcome of this phase is a comprehensive dataset of body landmark positions, which provides the foundation for subsequent kinematic analyses, such as joint angle computation and movement parameter extraction.

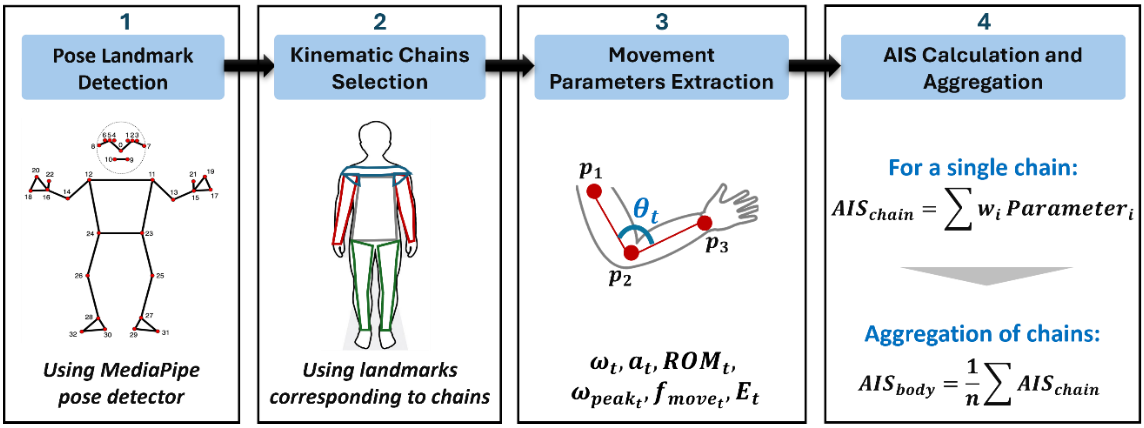

Figure 1. Proposed activity intensity estimation framework

2.2 Kinematic Chain Selection and Joint Angle Computation

In this phase, specific body segments, or kinematic chains, are defined, and joint angles are computed to analyze movement patterns. Kinematic chains represent interconnected body segments that work together to perform complex movements [21], [22]. In this study, the kinematic chains considered include the arms, legs, spinal segment, and other significant body segments, such as the neck and shoulder girdle. These chains are selected because they effectively capture the primary movements and joint dynamics of the human body, which are most relevant for assessing activity intensity in indoor environments. Table 1 provides an overview of the kinematic chains used in this study and the corresponding landmarks selected for each chain.

Each kinematic chain is defined by selecting three key landmarks that form two segments meeting at a joint. For example, the arm kinematic chain is defined by the shoulder, elbow, and wrist (see Figure 2), where the angle at the elbow joint is computed to represent arm movement. Joint angles are calculated using vector mathematics, with vectors formed from the selected landmarks. The joint angle (θ) is computed using Equation (1).

$$\theta = arccos\left(\frac{(p_1 - p_2).(p_3 - p_2)}{|p_1 - p_2| \times |p_3 - p_2|}\right) \qquad (1)$$

Where p_1 , p_2 and p_3 are the joints in the corresponding chain. This calculation yields the angle at the intersection of these segments, which provides insight into the movement pattern of the body.

Table 1. Kinematic chains and corresponding landmarks used in the study

Kinematic chain	Landmarks selected
Arm (Left)	Left Shoulder, Left Elbow, Left Wrist
Arm (Right)	Right Shoulder, Right Elbow, Right Wrist
Hand-Wrist (Left)	Left Elbow, Left Wrist, Left Index
Hand-Wrist (Right)	Right Elbow, Right Wrist, Right Index
Neck-Head	Shoulder Center, Neck, Head
Shoulder Girdle	Left Shoulder, Spine, Right Shoulder
Torso	Shoulder Line, Hip Line
Spinal	Hip Center, Shoulder Center, Neck
Leg (Left)	Left Hip, Left Knee, Left Ankle
Leg (Right)	Right Hip, Right Knee, Right Ankle
Lower Leg (Left)	Left Knee, Left Ankle, Left Foot Index
Lower Leg (Right)	Right Knee, Right Ankle, Right Foot Index
Full Body	Head, Spine, Feet

The rationale behind using kinematic chains is that they allow for a more detailed understanding of human movement by focusing on specific body segments. By analyzing the joint angles of these chains, we can effectively capture the intensity and dynamics of movement, which is crucial for applications like HVAC control that depend on accurate assessments of occupant activity levels. This phase yields time series of joint angles for each selected kinematic chain, which will be used in the subsequent phases to extract movement parameters and compute the AIS.

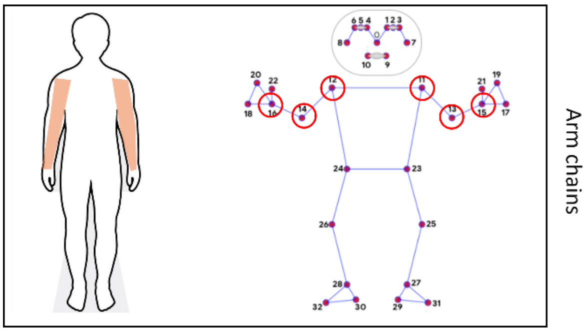

Figure 2. Illustration of sample kinematic chains and the selected landmarks from MediaPipe

2.3 Movement Parameter Extraction and Normalization

The third phase involves the extraction of key movement parameters from the joint angle data and their normalization for AIS computation. The goal is to derive meaningful metrics that reflect the movement intensity of different body segments. The following key parameters are derived, each representing a particular aspect of the activity intensity.

2.3.1 Angular Speed

Angular speed is computed as the first derivative of joint angles with respect to time, representing how quickly a joint angle changes. Since we have discrete angle measurements at each frame, numerical differentiation is used (see Equation (2)).

$$\omega_t = \left|\frac{\theta_t - \theta_{t-1}}{\Delta t}\right| \tag{2}$$

Angular speed captures the velocity of rotational movement, providing insight into the dynamic nature of the activity. High angular speed indicates rapid movement, contributing significantly to the overall activity intensity.

2.3.2 Angular Acceleration

Angular acceleration is the rate of change of angular speed, computed as the second derivative of joint angles with respect to time. Again, since we have discrete data, numerical differentiation is used (see Equation (3)).

$$\alpha_t = \left|\frac{\omega_t - \omega_{t-1}}{\Delta t}\right| \tag{3}$$

Angular acceleration measures sudden changes in movement speed, highlighting periods of rapid acceleration or deceleration. This parameter helps to identify bursts of activity that contribute to increased intensity.

2.3.3 Range of Motion

Range of motion (ROM) is defined as the difference between the maximum and minimum joint angles within a sliding window, as defined in Equation (4).

$$ROM_t = max(\theta_{t-\Delta t:t}) - min(\theta_{t-\Delta t:t}) \tag{4}$$

ROM represents the extent of movement for a specific joint. It indicates how much a joint moves during an activity. A higher ROM suggests more extensive movement, which is directly linked to higher activity intensity.

2.3.4 Peak Angular Speed

Peak angular speed is the maximum angular speed within a sliding window, presented in Equation (5).

$$\omega_{peak_t} = max(\omega_{t-\Delta t:t}) \tag{5}$$

Peak angular speed helps capture rapid bursts of movement that may not be reflected in the average speed. It is an important parameter for understanding the highest intensity levels within a given time frame.

2.3.5 Movement Frequency

Movement frequency is defined as the number of distinct peaks in the joint angle data within a sliding window. Equation (6) shows the movement frequency definition, calculated using peak detection algorithms.

$$f_{move_t} = Number\ of\ peaks\ in\ \theta_t\ within\ [t - \Delta t : t] \tag{6}$$

Higher movement frequency indicates more frequent changes in joint angles, which is often associated with increased physical activity levels.

2.3.6 Rotational Energy

Rotational energy is computed as the integral of the squared angular speed over a given time period. Since the data is discrete, it is calculated as the sum of the squared angular speeds, multiplied by the time interval, as presented in Equation (7).

$$E_t = \sum_{i=t-\Delta t}^{t} (\omega_i^2)\Delta t \tag{7}$$

Rotational energy provides a measure of the sustained effort involved in movement. It accounts for both the speed and duration of movement, making it a valuable indicator of overall activity intensity.

Each of these parameters is normalized to a scale between 0 and 1 using predefined expected ranges based on prior data. This normalization makes it possible for all the parameters to have equal contribution to the AIS irrespective of the range of their scales.

2.4 AIS Computation

In this phase, the AIS is computed by combining the normalized movement parameters. Each parameter contributes differently to the overall activity intensity, and as such, weights are assigned to each parameter based on their relative importance. These weights can be determined through expert consultation, sensitivity analysis, or empirical studies. The AIS for each kinematic chain and at each time frame is computed using the weighted sum of the normalized parameters, as defined in Equation (8), to provide a quantitative measure of activity intensity that reflects the combined effects of speed, acceleration, ROM, movement frequency, and rotational energy. $w_1, \ldots, w_6$ are weighting factors.

$$AIS(t)_{chain_i} = w_1(\omega_t)_i + w_2(\alpha_t)_i + w_3(ROM_t)_i + w_4(\omega_{peak_t})_i + w_5(f_{move_t})_i + w_6(E_t)_i \tag{8}$$

2.5 AIS Aggregation Across Kinematic Chains

The final phase integrates the AIS values from multiple kinematic chains to obtain an overall activity intensity measure. As defined in Equation (9), AIS values computed for all selected kinematic chains are aggregated for each time window, in this research using an average to compute the overall AIS. However, alternatively, a weighted average can be used if certain chains are deemed more influential. If certain kinematic chains are not detected, missed, or unavailable in the frame, their AIS values are excluded from the aggregation and average calculation. Alternatively, a weighted average can be used if certain chains are deemed more influential. The outcome of this phase is a unified AIS that represents the overall activity intensity at frame time, which can be used for thermal comfort prediction, dynamic HVAC control or other real-time applications. Here, N is the number of kinematic chains.

$$AIS(t)_{body} = \frac{1}{N}\sum_{i=1}^{N} AIS(t)_{chain_i} \tag{9}$$

3 Implementation

To test and validate the proposed AIS framework, a controlled data collection experiment was conducted to capture various movement intensities using a single standard camera in an indoor setting. The data collection was carried out at the North Dakota State University (NDSU) campus. A phone camera was positioned at waist height to ensure a full-body view, capturing video at 30 frames per second (fps). Three adults (two males, one female) were participated for the experiment.

To capture a range of movement intensities, participants were instructed to perform a set of predefined activities at low, moderate, and high intensities [14]. In this study, low-intensity included sitting, standing still, typing, and light stretching. Activities in moderate-intensity were walking at a regular pace, repeated arm movements, desk organizing, and dusting. Finally, heavy exercises like jogging in place, jumping jacks, push-ups, and squats comprised high-intensity activities [14], [23]. Activities were performed for approximately 80-90 seconds with a 1-minute rest interval in between to avoid fatigue. To enhance generalizability, participants performed different activities within each intensity level; for example, in the moderate-intensity category, one participant performed dusting, while another walked at a regular pace.

The selected activities are frequently observed in indoor settings, from workplaces to healthcare facilities, where real-time movement intensity estimation would be most applicable. They are common movements that reflect typical energy demands in such environments. For instance, a casual indoor pace (walking) contrasts well with intense exercises (jumping jacks). Furthermore, selected activities engage different body parts and movement dynamics. For instance, Sitting and Standing engage primarily the lower body and torso, while Jumping Jacks and Squats involve multi-joint movements. This diversity is beneficial to validate that AIS is responsive not just to movement intensity but to various kinematic patterns.

The AIS is calculated for each second (30 frames) of corresponding footage. For ROM, peak angular speed, movement frequency, and rotational energy, the time window is set on 30 timesteps (one second), while the instantaneous parameters (i.e., angular speed, angular acceleration) are calculated on the last frame of the past 30 frames. Weights in the AIS formula were chosen based on logical considerations of the role each parameter plays in characterizing movement intensity. Angular speed and acceleration are considered core parameters that directly reflect movement dynamics; hence they were given weights of 20 each. The remaining parameters—ROM, peak speed, movement frequency, and rotational energy—were each assigned a weight of 15, resulting in a total weight of hundred. Sample frames of the method implementation are shown in Figure 3.

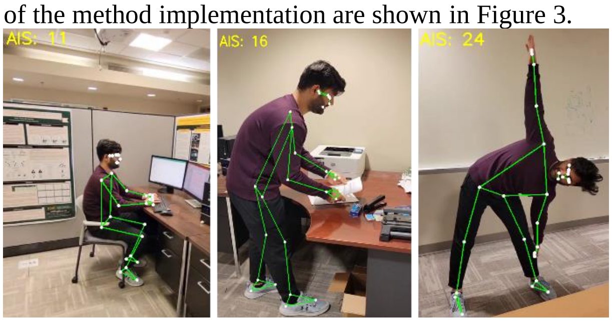

Figure 3. Implementation of the proposed approach on collected data (screenshots taken from videos). From left to right: light, moderate, and high intensity

4 Results

This section presents the findings of applying the proposed AIS estimation method on the collected data. Figure 4 illustrates the time-series plots of AIS values for a range of activities. Each plot shows the AIS variability across activities, highlighting clear differences in AIS between low-intensity, moderate-intensity, and high-intensity activities, for both participants.

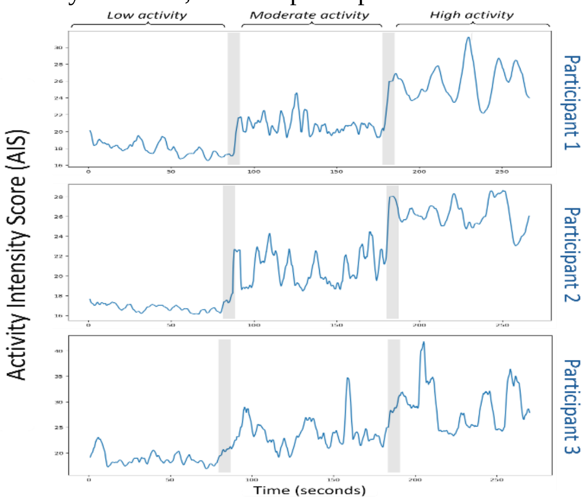

Figure 4. AIS values for different activities over time

These time-series graphs indicate that AIS values increase proportionally with activity intensity, which aligns with the purpose of the framework in capturing the expected differences in movement dynamics. To better confirm that, Figure 5 illustrates the average AIS across three participants for low, moderate, and high activity levels. The AIS increases as the activity level intensifies, confirming the method's ability to distinguish varying movement intensities. Small variations among participants reflect individual differences in movement styles (e.g., limb speed or range of motion). However, each participant shows a clear progression from low to high AIS values in accordance with activity intensity. These findings validate that the proposed AIS framework captures meaningful distinctions in movement intensity.

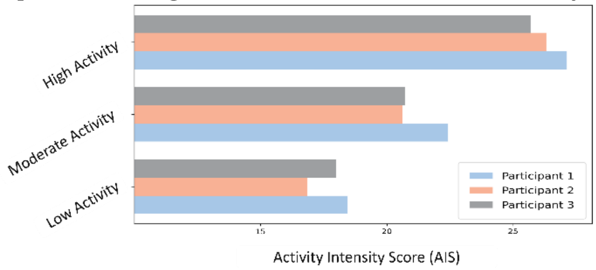

Figure 5. Mean AIS values for different activity levels

In addition, Figure 6 presents boxplots of the AIS constituent movement parameters across the three defined activity levels (for participant 1 as sample). These boxplots indicate a visual summary of the distribution of each parameter within each activity level and could illustrate the differences in movement characteristics associated with each activity level. The clear separation and trends observed among the boxplots suggest that both the AIS and individual movement parameters increase with higher levels of physical activity. This finding supports the validity of the AIS and its components as reliable indicators of activity intensity.

Finally, it should be noted that in some frames, not all kinematic chain landmarks could be detected by the pose estimation algorithm (see Figure 7). This issue primarily occurs when the subject is not fully visible from the camera angle. To address this anticipated limitation, the AIS calculation only includes kinematic chains that are fully detected in the corresponding frame.

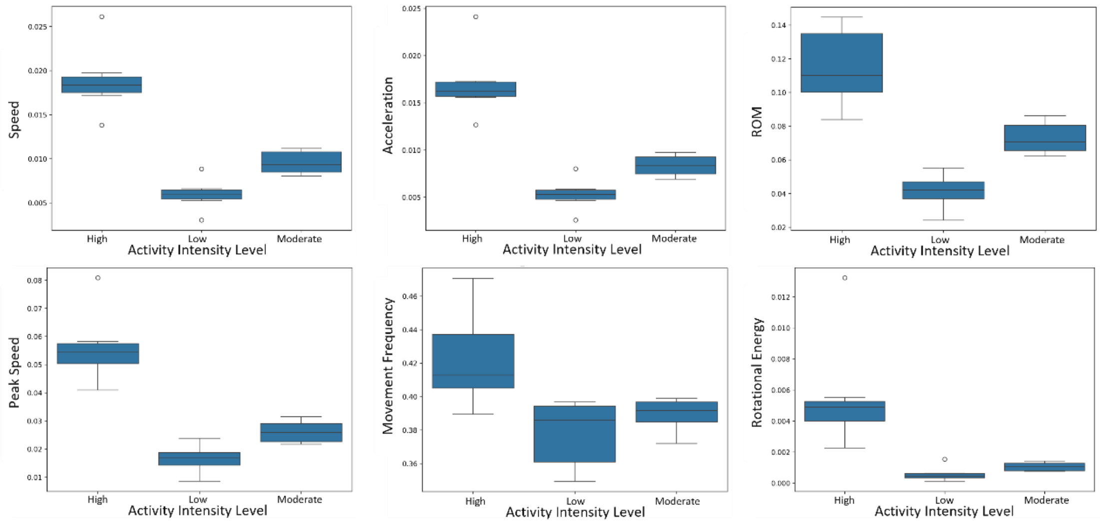

Figure 6. Distribution of AIS parameters within each activity level (normalized values)

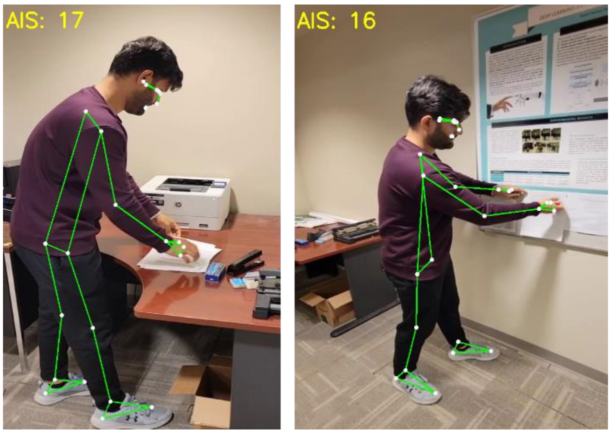

Figure 7. Missed pose landmarks (Left: left hand not detected; Right: left leg not detected)

5 Discussion

The results indicate that the proposed AIS framework effectively captures variations in human activity intensity and distinguishes between low, moderate, and high activity levels across different participants. The estimated AIS provides a real-time measure of occupant movement, which is crucial for optimizing HVAC systems by dynamically adjusting thermal conditions based on occupant activity levels. In the same conditions, higher activity levels generate more body heat, reducing the need for heating, while lower activity levels may require increased heating to maintain comfort. Therefore, AIS could be considered as an input factor when developing a thermal comfort prediction model to be utilized in HVAC control. On the other hand, integrating AIS alone may not be sufficient for HVAC optimization. Other factors, such as the duration of activity (to distinguish brief movements from sustained exertion), occupants' body temperature, and occupants' clothing insulation level should be considered. Future work could incorporate these factors alongside AIS to develop a more adaptive and efficient HVAC control strategy.

Although this study provided significant findings, some challenges remain to be addressed in future research. One limitation is the reliance on a single camera, which can lead to occlusion issues and missing pose landmarks [24], [25]. Additionally, the current framework uses a standard camera, which might raise privacy concerns for some users. Using thermal cameras is a potential solution to these privacy issues. Furthermore, future work could focus on optimizing the weights of AIS parameters.

6 Conclusion

In this study, a novel Activity Intensity Score (AIS) framework was developed to provide a continuous, real-time estimation of human movement intensity in indoor environments. The AIS integrates various kinematic parameters, including angular speed, acceleration, range of motion, movement frequency, and rotational energy, into a single measure that reflects the intensity of movement. Experimental validation confirmed the effectiveness of AIS in differentiating movement intensities, demonstrating its potential for applications such as adaptive HVAC control, ergonomic assessment, and health monitoring. While the framework offers a non-intrusive and scalable approach, future work should focus on improving robustness against occlusion, optimizing AIS parameter weights, and integrating additional physiological signals to further enhance its accuracy and practical implementation.

Acknowledgement

The authors express their gratitude to the funding provided to support this study from National Science Foundation (NSF) EPSCoR RII Track 2 Program under the grant number OIA-2119691. The findings and opinions expressed in this article are those of the authors only and do not necessarily reflect the views of the sponsors.

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