Indoor Personnel Thermal Comfort Monitoring System Design Based on Mobile Robots

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Abstract

With the development of smart buildings, people's requirements for indoor environmental comfort are becoming increasingly higher. Studies have shown that non-invasive infraredography (IRT) technology can effectively predict thermal comfort. This paper explores the use of mobile robots to monitor the thermal comfort of indoor occupants. Mobile robots can collectant information from multiple angles, and can locate and estimate the thermal comfort of occupants in real time. This paper first illustrates the importance of thermal comfort to the indoor and how environmental factors affect comfort. It then studies the design scheme of the robot system. Finally, experiments are conducted to evaluate the accuracy and reliability of the data by the robot, and the experimental results are analyzed.

Keywords: Dynamic hermal comfort, Intelligent building, Robot system, Infrared thermal imager

1.Introduction

In modern times, technology is rapidly advancing, and the field of architecture has also seen significant progress, with smart buildings becoming a prominent trend, the way we interact with and manage indoor spaces. The core of smart buildings lies in their ability to closely monitor and control the indoor environment, where thermal comfort is key factor that directly affects the health and productivity of occupants.

The traditional approach to assessing thermal comfort in indoor environments has relied on placing fixed sensors at specific locations. Although these sensors can serve their purpose, their fixed positions limit the range of data collection, often resulting in incomplete coverage of the entire indoor space. Additionally, they lack the adaptability needed to account for the dynamic changes in the room's occupancy patterns and the distribution of occupants.

To address these issues, mobile robots can be used to monitor indoor thermal comfort. With their mobility and flexibility, mobile robots offer a novel solution to the challenges faced by traditional sensing methods[1]. They are equipped with thermal imaging cameras and environmental sensors that enable data collection from multiple vantage points within the indoor environment. The thermal imaging camera, with its high resolution and wide field of view, can capture detailed thermal images of occupants, providing information about their surface body temperatures. Meanwhile, the environmental sensors, which measure parameters such as temperature, humidity, and air speed, offer real-time data about the environmental conditions prevalent in the room.

Combining thermal imaging data with environmental data can more accurately evaluate thermal comfort and calculate the Predicted Mean Vote (PMV) thermal comfort index, is widely recognized and used in the field of indoor environmental quality assessment.

The remainder of this paper is organized as follows. Section 2 provided a detailed description of the hardware aspects of the system design. Section 3 focuses on the functional modules of the robot system, showing the operation of each software part in the entire system. Section 4 presents preliminary experiments and analyzes the experimental to explore the impact of the collected data on understanding thermal comfort and its determinants. Finally, Section 5 concludes the main findings and outlines potential directions for future in the field.

2.System Design

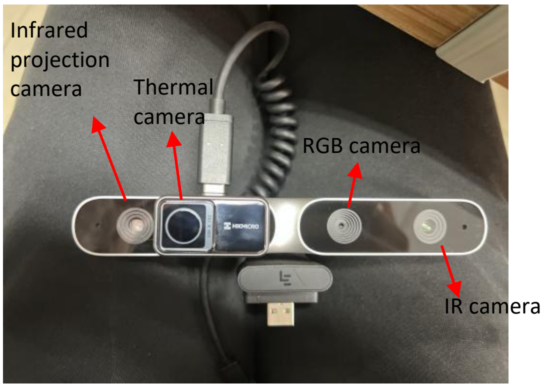
The proposed system is meticulously crafted with a comprehensive and in-depth consideration of a multitude of factors, all of which are essential to guarantee its optimal effectiveness and unwavering reliability in the crucial task of monitoring the thermal comfort of indoor personnel. This undertaking involves a holistic approach that takes into account not only the technical aspects but also the practical requirements and challenges associated with operating within an indoor environment.

The mobile robot, for instance, is not just a simple vehicle but a sophisticated platform that combines mobility with a suite of sensing capabilities. Its design is optimized to balance the need for compactness, which allows it to navigate through tight spaces and around obstacles commonly found in indoor settings, with the requirement for housing and powering a range of sensors and processing units.

This system not only provides real-time data on the thermal comfort levels of occupants but also offers actionable insights that can be used to optimize the indoor environment, enhance occupant well-being, and improve energy efficiency.

2.1. Mobile robot platform

The mobile robot used in this study is a platform with a compact design. It is equipped with a high-resolution infrared thermal imaging camera and a suite of environmental sensors, including temperature, humidity, and air velocity sensors. The robot is controlled by an onboard microcontroller, which enables it to navigate autonomously within the indoor environment. The infrared camera has a wide field of view and can capture detailed thermal images of occupants. The environmental sensors provide real-time data on the ambient conditions, which are used in conjunction with the thermal images to assess thermal comfort. The hardware part for robots to acquire external information is shown in Fig.1.



a.The visual components of the robot

b. Mobile base with temperature and humidity ,wind speed detection module

Fig. 1. The hardware part for robots to acquire external information.

2.2. Data acquisition and processing

The data collected by the robot is transmitted to a central server for processing, via both wired and wireless means. The server uses image processing algorithms extract thermal information from the images, such as the surface temperature of the occupant. Environmental data is also integrated into the analysis, to account for the impact of temperature, humidity, and wind speed on thermal comfort. The processed data is used to calculate the thermal comfort index, or Predicted Mean Vote (PMV)[2]. As shown in Table1, the thermal sensation labels are represented in seven levels.

Table 1

Thermal sensation labels.

Thermal sensation	Label
Uncomfortable warm	3
Warm	2
Slightly warm	1
Comfortable	0
Slightly cold	-1
Cold	-2
Uncomfortable cold	-3

3.Introduction to System Modules

With the help of these functional modules, we can achieve personnel thermal comfort monitoring.

3.1. Multi-passenger facial recognition

To avoid the problem of duplicate calculations during the robot's room patrol, a method for multi-occupant facial matching and recording was.

The facial detection algorithm Multi-task convolutional neural networks(MTCNN) identified the facial regions in the image frame. MTCNN is a multi-task cascaded deep learning network that integrates bounding regression and feature point selection to achieve facial recording and matching. Before performing facial matching, facial embedding is an essential step that allows the matching algorithm to focus on the features of the image. Facenet is an extraordinary embedding algorithm, especially in facial matching. It can directly map the face to a high-dimensional vector in Euclidean. Matching vectors in Euclidean space to determine if they are from the same person. In general, vectors from the same person are very close in Euclidean space while vectors from different people are far apart. The method of calculating the Euclidean distance of vectors is:

$$\text{vectorX} = [x1, x2, \ldots, xn] \tag{1}$$

$$\text{vectorY} = [y1, y2, \ldots, yn] \tag{2}$$

$$\text{EuclideanDistanceXY} = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

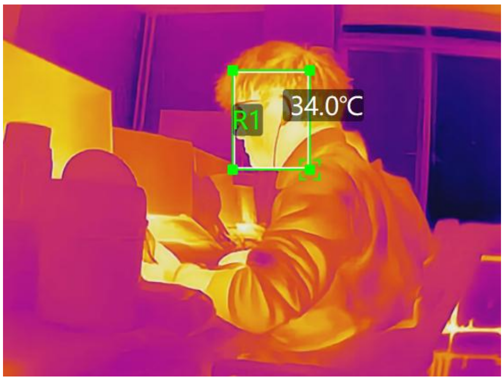
Here we set the threshold to 1.242 according to the Euclidean distance computation criterion. If the Euclidean distance between the two vectors is less than 1.24, then the two face bounding boxes are considered to be from the same person, and the face match is successful. Otherwise, it means they may come from people, and the faces do not match.

If the facial image matches the observed human face, the ID is labeled with the unique number of this person. If the facial image does not, a new number is registered in the dataset, and the facial image is labeled with that number. Finally, the detected facial image is added to the dataset for matching. However, when we record the detected images with a mobile robot, the dataset grows too large to match. To match quickly, we only record two facial with the closest Euclidean distance for each person.

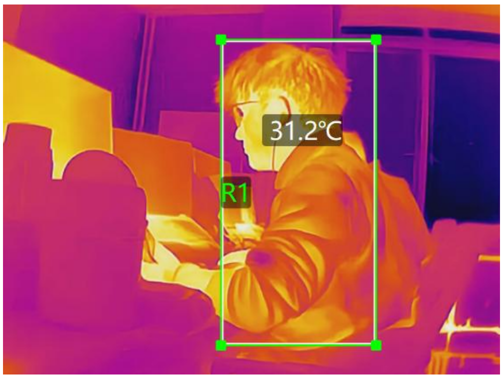
3.2. Infrared temperature measurement module

To obtain human thermal comfort, body temperature is indispensable. We used the YOLOv8 human recognition model in combination with an infrared imager to measure the temperature of the human body trunk and face respectively. The experimental results show that using facial temperature instead of body temperature is more accurate and better the thermal sensation of the person. The contrastive experiment is shown in Fig.2

Therefore, the system uses the YOLOv8 deep learning model for facial recognition, and obtains thermal image data in real through a thermal imaging camera[3]. The obtained thermal images are preprocessed to meet the input requirements of the trained model, and then the images are fed into the model inference. The model outputs the bounding box location and temperature prediction value of the face, and the system uses this information to perform visual annotation on the image, showing location of the face and the predicted temperature. The facial temperature measurement of the thermal image is shown in Fig. 2(a)



a.Facial thermal image



b.Body thermal image

Fig. 2. Infrared thermal image

3.3. *Human body attribute recognition module*

The robot system is embedded with a series of convolutional neural networks to recognize human characteristics, including age, gender, pose, and. The BodyPix model is applied to segment the human body from the background, and then convolutional neural networks are used to identify the characteristics of the occupant The model is based on the Yolov8 object detection network and is trained with the Adience dataset, which contains 29,000 images It can simultaneously recognize information about a person's gender, age, and body pose. However, different people can have significant differences in appearance at the same age, it difficult to predict exact age solely by analyzing a person's image. Therefore, it only predicts possible age ranges in five groups (14-17,18-26, 27-35, 36-42, and over 42). The clothing recognition model is based the Yolo-v5 object detection network and is trained with the DeepFashion2 dataset, which contains images of various clothing. Clothing is categorized from thin to thick seven levels, including short-sleeve shirts, shorts, long-sleeve shirts, long pants, sweaters, coats, and down jackets. These models are and can be embedded in the robot's system for real-time computation.The test results are shown in Fig.3.

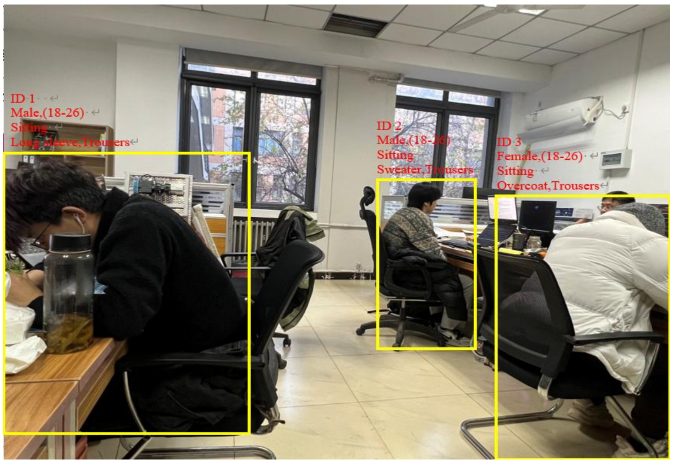


Fig 3. Human body feature detection

3.4. Robot path tracking and thermal comfort distribution

There are two parts working together in this module. One is the global positioning and tracking of the robot, and the other is the positioning the human. The former detects surrounding objects and spatial layout by emitting laser pulses from the LiDAR and measuring the time it takes for these pulses to bounce back This information is then used to build a three-dimensional map of the environment. With the environmental map and its own positioning, the robot can use the path planning Dijkstra algorithm to calculate the optimal path from its current position to the target position. At present, we mark five points on the main road in the room for the robot move in a loop, achieving comprehensive detection of the room environment. The latter is to estimate the position of the human body relative to the robot. In this part, RGB images and depth are collected synchronously to show the distance between the person and the camera, which is used to build a three-dimensional point cloud of objects in the camera view and three-dimensional coordinate $(x_c,\ y_c,\ z_c)$ in the robot view. The body relative coordinates are then converted to global coordinates (x_g , y_g , z_g) through the rotation matrix R and the translation vector t as follows:

$$\begin{bmatrix} x_c \\ y_c \\ z_c \\ 1 \end{bmatrix} = \begin{bmatrix} R_{3\times3} & 1_{3\times1} \\ 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} x_g \\ y_g \\ z_g \\ 1 \end{bmatrix}. \quad (4)$$

When a new view is received, the facial detection and localization function is triggered. As extracting features from the model is time-consuming, the feature function runs ten times a minute on the collected personnel image segmentation. The thermal comfort prediction function is triggered when the feature attributes have been fully collected or some attributes have updated. The room mapping function is triggered when the robot is on the move, displaying the predicted thermal comfort on the map in real-time.

4. Prediction of Thermal Comfort and Experiment

4.1 Thermal comfort prediction algorithm

Danish scholar Professor Fanger took into account several factors affecting human comfort, established the thermal comfort sensation evaluation index equation through relevant data analysis, and proposed the PMV representing human cold and hot sensation, its computational formula is:

$$\mathrm{PMV} = [0.303\exp(-0.036\mathrm{M}) + 0.0275]\mathrm{TL} \quad (5)$$

$$\begin{aligned} TL = {} & (M-W) - 3.05[5.733 - 0.007(M-W) - P_a] \\ & - 0.42(M - W - 58.15) \\ & - 1.73 \times 10^{-2} M(5.867 - P_a) \\ & - 1.4 \times 10^{-3} M(34 - t_a) \\ & - 3.96 \times 10^{-8} \times f_{ct}[(t_{ct} + 273)^4 \\ & - (t_r + 273)^4] - f_{cl} h_c (t_{ct} - t_a) \end{aligned} \quad (6)$$

However, the mathematical expression of the PMV thermal comfort index he uses has the disadvantages of complex computation and inaccurate results, and cannot used as a control variable for real-time control of indoor equipment. Therefore, this project adopts a PMV prediction model based on BP neural network[4]. BP network is a multi-layer feedforward network that continuously trains samples to adjust the network's weights and thresholds, minimizing the error between the output value and the desired value The network mainly consists of an input layer, an intermediate layer, and an output layer, and it is trained through forward signal propagation and backward error propagation.

To improve the slow convergence speed of traditional BP neural networks, the bird flock algorithm is used to optimize the initial weights and thresholds of the BP neural network. The bird algorithm is a new type of optimization algorithm that not only has the advantages of the particle swarm optimization (PSO) algorithm but also effectively avoids premature convergence due to diversity. Therefore, this project uses the bird flock algorithm to optimize the BP neural network, and uses this model to predict the PMV of the indoor environment.

4.2. *Experiment and data analysis*

The experiment was conducted in a controlled indoor environment, such as an office or laboratory. The room was equipped with heating, ventilation, air conditioning (HVAC) to maintain a stable environmental temperature. Mobile robots were deployed in the room and programmed to move along a predetermined path, periodically collecting and environmental data. The thermal images were used to measure the surface temperature of the occupants, and the environmental data were used to calculate the thermal comfort index. The thermal comfort was visualized as different colors on a map, and finally, a thermal comfort distribution map of the room was generated, as shown in Fig.4 All occupants were dynamically added to the global map with color-coded estimated thermal comfort. We conducted a questionnaire survey to compare the optimized BP neural network prediction algorithm with traditional methods, asking whether the PMV values were consistent or close to the subjective thermal comfort ratings provided by the occupants. The survey results were summarized and Table2 after the experiment. The results show that the system is capable of accurately detecting changes in thermal comfort caused by changes in environmental conditions. Our experiments recorded the feature results of multiple indoor individuals, as shown in the Fig 5, proving the validity and accuracy of the model.

Table 2

Prediction accuracy.

Group number	BP algorithm	Traditional
1	92%	74%
2	88%	69%
3	96%	78%
4	92%	66%
5	86%	60%

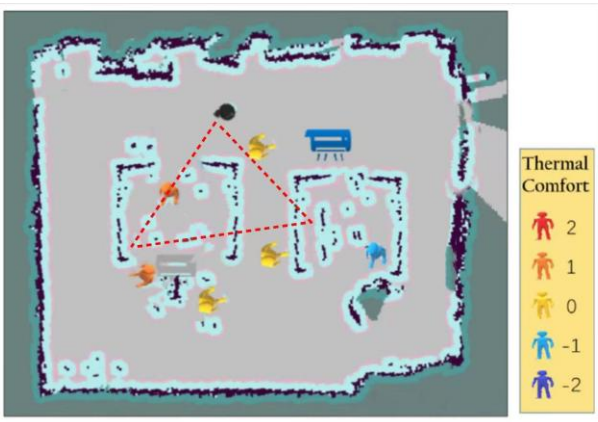


Fig 4. Thermal comfort distribution

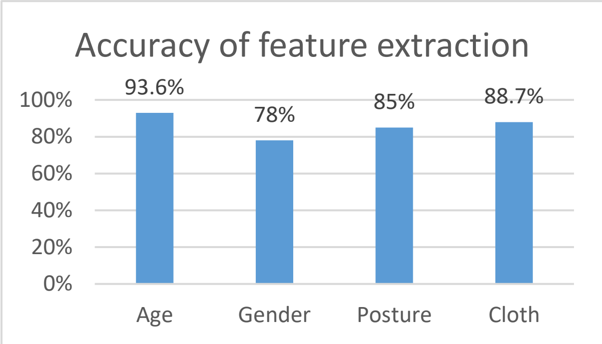


Fig 5. Results of human feature extraction.

4.3. *Future development direction*

The data collected by the mobile robot provides valuable insights into the thermal comfort of indoor occupants. By analyzing the relationship between the body surface temperature, environmental factors, and thermal comfort indices, it is possible to identify the factors that have the greatest impact on thermal comfort. This information can be used to optimize the HVAC system settings to improve occupant comfort and energy efficiency. For example, if the analysis shows that a particular area of the room is consistently experiencing discomfort due to high temperatures, the HVAC system can be adjusted to provide more cooling in that area.

5. Conclusion

This paper presents a system based on mobile robots for real-time monitoring of indoor occupants' thermal comfort. The experimental results show that the system can and accurately evaluate thermal comfort. Future work will focus on improving the accuracy and reliability of the system, as well as integrating it with other building management systems to achieve comprehensive environmental control, allowing the indoor environment to actively adjust to enhance occupant comfort and health.

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