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Non-invasive (non-contact) measurements of human thermal physiology signals and thermal comfort/discomfort poses -A review

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A B S T R A C T

Heating, ventilation and air-conditioning (HVAC) systems have been adopted to create comfortable, healthy and safe indoor environments. In the control loop, the technical feature of the human demand-oriented supply can help operate HVAC effectively. Among many technical options, real time monitoring based on feedback signals from end users has been frequently reported as a critical technology to confirm optimizing building performance. Recent studies have incorporated human thermal physiology signals and thermal comfort/discomfort status as real-time feedback signals. A series of human subject experiments used to be conducted by primarily adopting subjective questionnaire surveys in a lab-setting study, which is limited in the application for reality. With the help of advanced technologies, physiological signals have been detected, measured and processed by using multiple technical formats, such as wearable sensors. Nevertheless, they mostly require physical contacts with the skin surface in spite of the small physical dimension and compatibility with other wearable accessories, such as goggles, and intelligent bracelets. Most recently, a low cost small infrared camera has been adopted for monitoring human facial images, which could detect the facial skin temperature and blood perfusion in a contactless way. Also, according to latest pilot studies, a conventional digital camera can generate infrared images with the help of new methods, such as the Euler video magnification technology. Human thermal comfort/discomfort poses can also be detected by video methods without contacting human bodies and be analyzed by the skeleton keypoints model. In this review, new sensing technologies were summarized, their cons and pros were discussed, and extended applications for the demand-oriented ventilation were also reviewed as potential development and applications.

Contents

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1. Introduction

Building energy supply and indoor environmental conditioning should be performed in demand base and intelligent manner. Nowadays, building centered design has been changed to human centered design. Terminology, such as the human building integration, was frequently mentioned. Traditional methods of controlling thermal environments rely on research performed on human subjects in controlled, often unrealistic, environments. The temperature settings are the building operator's best guess of conditions that will lead to the highest degree of thermal comfort (subject to the limitations of equipment and budget). The selected conditions are derived from a long history of thermal comfort measurements (and then adjusted to accommodate the complaints and requests of the occupants).

Traditional sensor based environmental parameters' measurements were not accurate enough because sensors are normally located in one location and indoor environmental parameters are spatially non-uniform. The survey-based questionnaire method interrupts occupants frequently, although it can obtain occupants' feedback to surrounding thermal environments directly. With the development of image/video processing technologies, more non-contact image/video sensing methods were used. In this review, traditional invasive measurements are reviewed in Section 3. Semi and mini invasive measurements are reviewed in Section 4. Non-invasive measurements, including the infrared camera technology, Euler video magnification technology; and the skeleton keypoints technology, are reviewed in Section 5. Extension applications of the skeleton keypoints technology for the demand oriented ventilation are discussed. Major achievements and future development are presented at the end of this review. Main contents are summarized in Table 1. Publication search was performed in the following databases: PubMed, Web of Science, Science Direct, Scopus, Wiley Online Library and Google Scholar. The following keywords were combined to retrieve relevant publications: non-invasive measurement, non-contact measurement, occupant thermal comfort, infrared imaging, machine learning, wristband, Euler video magnification, skeleton keypoints, and thermophysiological sign. The search period covered 2000–2020.

Before the review content, the tiny difference between non-invasive measurements and non-contact measurements should be clarified. In the medical field, non-invasive measurement is defined as any measurement does not require physically break the skin or enter the human body deeply through an external orifice. In contrast, for thermal comfort research, a non-invasive measurement is usually defined as any measurement system/protocol to acquire thermal comfort effectors that does not intervene occupants' activity. Thus, physiological measurements such as body temperature measurements using thermometers in the ear canal, mouth or rectum are considered as invasive in thermal comfort research whereas they are considered as non-invasive from a medical field perspective. Similarly, measurements of the electrical output of human activity such as electrocardiogram (ECG), electropalatogram (EEG), electromyogram (EMG) and electrooculogram (EOG) are invasive. Non-contact measurements are defined as the acquisition of human thermal comfort data or information without touching the body. For instance, remote sensing techniques such as the infrared camera system are truly both non-contact and non-invasive. Obviously, non-contact measurements do not necessarily be non-invasive. Hence, the term "non-contact" is more commonly used in the literature regarding non-contact measurements.

2. Traditional invasive (contact) measurements

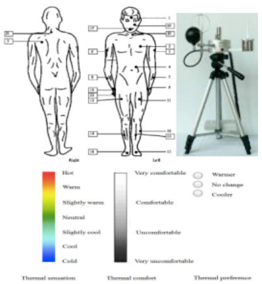
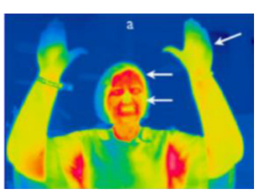
Traditional invasive (contact) measurements include surveys, physiological measurements and environmental measurements. A survey, typically in the form of questionnaire, is the most direct method because it extracts occupants' state of mind with regard to thermal environments. Surveys are invasive because they require the occupants to temporarily cease their normal activities and fill out the surveys or respond to electronic inquiries. Paper-based surveys are mainly used for lab tests and are not feasible in real built environments where both the thermal conditions and the occupants may be constantly changing. Computer based electronic questionnaires[48]and cell phone based apps can be used but they need continuous and frequent user feedback[12]. Measurement results of environmental parameters are not direct feedback or physiological signals from human occupants. Correlation between environmental parameters and occupant feedback can be created by supervised learning methods, which is used for thermal comfort assessment in the absence of occupant feedback[66]. Location difference between environmental sensors and occupants, non-uniform distribution of air temperature, speed and solar radiation, are main challenges[8,9].

Physiological measurement can be correlated with thermal comfort/discomfort[17,64,39]. Invasive (contact) methods, for measuring skin temperature, skin blood flow, core temperature, heart rate, heart rate variability, electroencephalograph (EEG) and so forth, are commonly used. Measuring errors are caused by angle and position of device, movement and limb fat content of occupant [76]. Foreign body sensation is the main obstacle for practical measurements.

3. Semi and mini-invasive (contact) measurements

Unlike traditional invasive methods require physically body contact, semi and mini invasive methods were presented by integrating sensors into wearable accessories. Four infrared sensors were integrated to eyeglasses to extract the skin temperature from the front face, cheekbone, nose and ear for thermal comfort assessment and thermal regulation performance analysis [9]. Based on the results, a hidden Markov model based learning method was developed[10] to capture individual thermal comfort. The method could continuously monitor real time thermal comfort of individual occupants. Nevertheless, the method did not consider the effect of occupant activity intensity on thermal comfort. Besides, how the

Table 1
Contact, semi and mini-contact and non-contact measurements.

Cases	Methods	Main Contributions	Merits	Limitations	Selected References
	Traditional contact measurements	Questionnaire survey, environmental parameter measurement and physiological parameter measurement were used to evaluate human thermal comfort.	Accuracy Proved by many studies	Continuous and frequent feedback is needed for questionnaire survey. Environmental parameters are not direct feedback or physiological signals from human occupants. Foreign body sensation is the main obstacle for physiological parameter measurement.	[17,48,64,76,8,9]
	Semi and mini-contact measurements	Integrating infrared sensor to glasses to measure human physiological parameters, a semi-invasive human thermal comfort measurement scheme was proposed. Wrist-type wearable devices, such as smart bracelet, can be used to measure wrist skin temperature, pulse rate variability, etc.	Accuracy Less disturbance for the people	1. Not all people wear glasses and wrist-type wearable devices. 2. The sense of foreign body is weakened but not eliminated. 3. The allowed ambient thermal ranges are limited for accurate sensing.	[9,65,10,43,38,72]
	Non-contact measurements (infrared camera technology)	Infrared images of bare skin (such as face skin and hand skin) were collected and analyzed by infrared camera and used to evaluate human body thermal comfort.	No contact Comprehensive information for multi-people and surroundings	Infrared cameras are usually high cost and big size.	[25,55,51,41,52,15,28,71,32,35]

(*continued on next page*)

Table 1 (*continued*)

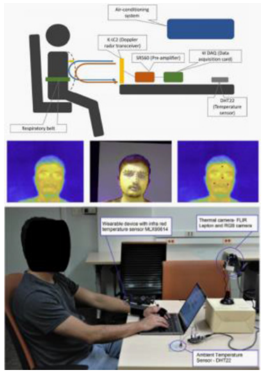
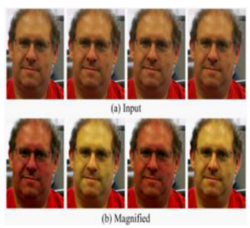
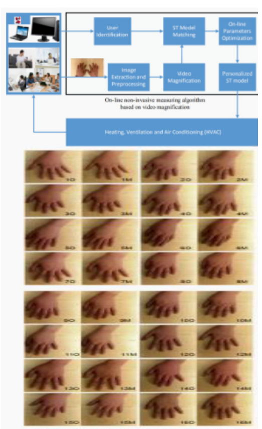
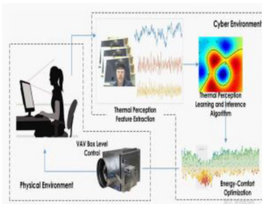
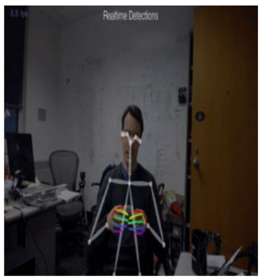
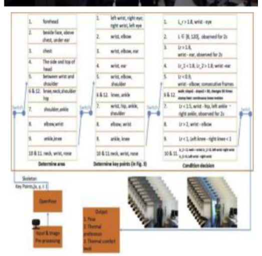
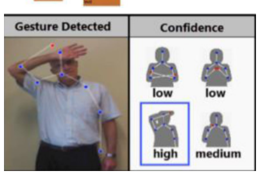
Cases	Methods	Main Contributions	Merits	Limitations	Selected References
	Non-contact measurements (cross-validation of infrared camera, RGB camera and wearable devices)	The reliability of semi-contact and non-contact measurement of human thermal comfort was cross validated.	No contact Accuracy		[6,3,7,5,72]
	Euler video magnification	Euler video magnification, a technology that enlarges frames in a video to show subtle movements and color changes that are invisible to the naked eyes, was officially proposed. Euler video magnification can be used for structural detection, judging whether the sound is vocal by enlarging the laryngeal node, detecting slight changes in heart rate, pulse, human skin color, and blood flow.	Providing heart rate		[18,36]
	Non-contact measurements(ordinary camera combined with Euler video magnification)	Euler video magnification was firstly used to monitor human thermal comfort and control HVAC system. A preliminary experiment of non-contact measurement was carried out under the condition of weak stimulation of human hand in 45 °C warm water.3. The skin image was trained by using big data and the NIDL algorithm.4. The skin sensitive index, which is an index to evaluate the non-contact measurement scheme, was proposed		1. The subjects are only Asian women, and the experiment needs to be further verified. 2. The experiment was only performed under strong stimulation conditions	[75,74]

Table 1 (*continued*)

Cases	Methods	Main Contributions	Merits	Limitations	Selected References
	Non-contact measurements(ordinary camera combined with Euler video magnification)	Human body is weakly stimulated at different ambient temperatures (high temperature 30 °C low temperature 20 °C), and facial images are extracted for analysis. A thermal comfort evaluation scheme was proposed, which combines commercial camera and RGB video image technology. The video post-processing technology was explored to eliminate the influence of interference areas and artifacts.		The influence of human movement and background light is unavoidable.	[70,26,69]
	Skeleton keypoints model	Dynamic poses can be captured in real time. Multi-person and single-person pose estimation based on deep learning was proposed. It was widely used in different fields, such as video games, robotics, medical science, etc.			[54,77,62]
	Non-contact measurements method (Skeleton keypoints mode)	The twelve poses of thermal discomfort was defined. An algorithm was proposed to associate thermal uncomfortable poses with thermal uncomfortable feeling.	No contact Detailed information about human pose	In a short time, the number of frames available for pose determination is insufficient, which causes a misjudgment at the first one to two seconds of pose switching.	[16]
		Four thermal discomfort related poses were defined. Library of thermal discomfort poses was established.		The Kinect is protected by many patents and its application scope is limited.	[11]
	Application of non-contact measurements in demand oriented ventilation	A new image based indoor personnel positioning and pose recognition system was set up. The method can be used for detecting operating modes of multi-functional rooms (classroom/conference room) and controlling demand oriented ventilation systems.	Accurate human position and pose Easy system setup Low system cost	3D reconstruction accuracy need to be improved.	[34]

factors such as optimal positions, distancing and sensing coverage affect the prediction accuracy of thermal comfort remained unknown.

Wrist-type wearable devices, such as smart bracelet, can be used to measure the wrist skin temperature[23,50]. Skin temperatures from three different wrist parts were monitored on sedentary occupants under different room temperatures, together with fingertip skin temperature measurements[65]. A thermal comfort estimation model was developed. A wristband was used to record photoplethysmogram (PPG) signals, from which Inter-beat interval (IBI) signals were extracted and sent to a smart phone for pulse rate variability (PRV) calculation and real time thermal comfort prediction[43]. The wristband was also used to dynamically correct offset errors for thermal images captured by smartphone thermal cameras[35]. Measuring results of skin temperature and heart rate (HR)/heart rate variability (HRV) from smartwatch were used to develop thermal sensation estimation models[20,21] . They were also compared with results from professional measuring devices [27]. In spite of good estimations of the thermal sensation perception were found based on the wrist skin temperature/hear rate and proposed models, most models were validated on a limited number of occupants in specific thermal conditions. Besides, individual characteristics such as gender and fitness are not considered in those models.

4. Non-invasive (non-contact) measurements

Traditional invasive measurements, including a questionnaire surveys, monitoring of environmental parameters and human physiological parameters were widely used and integrated with Internet of Things (IoT), Artificial Intelligence (AI) and machine learning (ML). Minimized measuring sensors are more user-friendly to occupants. Sensors were also integrated into wearable accessories, such as goggles, watches, to avoid potential foreign body sensations.

Video and image methods were tried to achieve non-contact measurements. Presently, three research directions were developed, including the miniaturization and low-cost of infrared camera technology, the Euler video magnification technology-aided normal camera for monitoring human thermal physiology signals, and the skeleton keypoints model aided normal camera for monitoring thermal comfort/discomfort poses.

4.1. Infrared camera technology

Before being used for the occupant thermal comfort assessment, videos and images captured by infrared camera were widely used for emotion and expression recognition [19,46,24,4] , medical detection[55,45,40] , face recognition and landmarking [57,61,44,56] , lie detection[37,78,63] , and so forth.

Infrared camera was widely used for collecting and analyzing infrared images of the nude skin such as facial, hand skin [55,51,41,52,15,28,71,32] , which may be used to infer how to control HVAC systems in an energy efficient manner without compromise of occupant thermal comfort [41]. Facial skin temperature was obtained by far-infrared imaging (7–14 μm). Other parameters, including skin potential, skin resistance, hand skin temperature, respiratory frequency and cardiac frequency can also be obtained and analyzed[25]. Recently, low cost and miniaturized models are commercially available, such as smartphone based thermal camera[29]. Compared to high-end models, the accuracy of low cost thermal camera is insufficient because of uncooled infrared detectors. A dynamic offset correction method was proposed[35]. Infrared camera technology was also compared with traditional invasive measurements of ambient air temperature and semi invasive measurements of wrist-type wearable devices [2]. Accuracy tradeoffs among them were analyzed. Results revealed that data combination from both physiological and ambient sensors resulted in 3–4% higher accuracy than using ambient sensors only. Thus, using physiological sensors might not be desirable in the studied conditions. To solve the issue of occupants' relative movements to thermal camera, a new approach was proposed to extract skin temperature by locating specific face regions in thermal images which combined data from RGB images with thermal images and leveraged facial landmark detection in RGB images [2]. Combination of different algorithms, including the face detection, facial landmark detection, emotion recognition, face frontalization and analysis, was tried to analyze infrared face images[53]. Infrared camera was also used for collecting and analyzing infrared images of athletes during outdoor running and indoor treadmill running[30]. Though above-mentioned studied showed good thermal sensation predictions with 65–85% accuracy, the effect of noise in thermal images on thermal and comfort modeling has not been examined. The robustness and precision of algorithms and models require further validation. In addition, privacy concerns on how to analyze and use data collected by infrared cameras are presented.

Three sensors, including a thermographic camera, a depth sensor and a color camera, were integrated into a sensing platform named RGB-DT (RedGreenBlue-DepthTemperature) to extract skin and clothing temperature for thermal comfort assessment[6]. The sensing platform followed three principles, which are low cost (USD 300), small form-factor device and real-time capabilities. Based on the methods, the machine learning method was used to generate prediction and perform data analysis [1],Chaudhuri et al., 2017; [7,5]. Infrared thermal camera network, composed by low-cost thermal cameras and RGB-D sensors (Kinect), was tried to overcome influences of occupants' postures and movements [72]. However, an infrared camera in thermal comfort and sensation predictions is still limitedly accurate in reality, mainly caused by users' dynamic postures and movements. Also, a potential privacy issue is still available by taking the identifiable facial image.

4.2. Euler video magnification technology-aided normal camera

A microscope-like visual motion magnification technique was presented, which combined the measured visual motion with pixels modified from a sequence of video images using the Lagrangian method to view the forms and characteristics of magnified motion in a video[18]. Euler video, a technology that enlarges frames in a video to show subtle movements and color changes invisible to the naked eyes, was officially proposed[36]. Unlike the Lagrangian method, Euler processing does not actually track motion, but rather relies on video pyramids and temporal processing that produce magnification. The basic method is to consider the time series of color values at any given pixel and amplify the changes in a given time band of interest.

Euler video magnification can be used for structural detection, judging whether the sound is vocal by enlarging the laryngeal node, detecting slight changes in heart rate, pulse, human skin color, and blood flow[67]. Subsequently, two research groups at Umeå University in Sweden and Virginia Tech University in the United States applied Euler video magnification for human skin temperature measurements which could reflect thermal comfort status and send feedback signals for controlling HVAC systems.

Based on subtle changes in blood vessels and skin colors, the relationship between the skin color saturation and the skin temperature was established[75]. A non-contact human skin temperature measurement technology that can be used as feedback signals for HVAC systems was proposed. The color of the human skin changes slightly with the expansion or contraction of blood vessels, especially under local thermal stimulation such as using a hand warmer. Although the changes are invisible to naked eyes, images captured by a common camera can be enlarged to analyze temperature changes. High blood vessel density on hand back is usually not covered by clothes. Skin of young female subjects is relatively delicate without skin wrinkles and sensitive to thermal stimulation. Therefore, east Asian women were chosen and their hands were stimulated in warm water at 45 °C for 10 min. After that, video was recorded and analyzed by magnification to obtain the hand back skin color saturation. Meanwhile, the hand back skin temperature was also measured. The relationship between skin color saturation and skin temperature was established for the purpose of measuring skin temperature in a non-contact way.

Euler video magnification technology can accurately analyze the skin color saturation. When skin temperature rises, pores expand and the skin becomes red. According to the Saturation-Temperature (ST) model, skin color saturation may have a linear relationship with the skin temperature. Red, green and blue (RGB) signals of skin colors were extracted and magnified. Independent component analysis (ICA) was used in video post-processing to remove noise and separate heart pulses for achieving automatic measurements of heart pulses. Through the vital sign camera algorithm, the rate of skin color change was enlarged to achieve accurate measurement of non-contact pulse and breathing frequency. Using the partly personalized ST model for non-contact measurement of the skin temperature of young women from East Asia, the median value of absolute error changed from 1.32 °C to 0.61 °C. The results demonstrated that the skin temperature signal can be obtained by using a common camera combined with the video amplification technology to achieve non-contact measurements of human temperature. The subtleness magnification and deep learning (NIDL) algorithm was proposed and cross-validation was performed using NIDL, partly personal ST model (NIPST) and iButton sensors, which further evaluated the feasibility of using Euler video magnification technology[73]. A non-contact skin temperature measurement method based on skin sensitivity index (SSI) was proposed, and deep learning network training was performed on skin images using big data[74].

Euler video magnification technology was developed from non-contact measuring the skin temperature under strong stimulation by water to weak stimulation by room air. A thermal comfort evaluation scheme using off-the-shelf commercial cameras (i.e., Logitech HD Pro Webcam C920) and RGB video image technology was proposed[26]. Under experimental conditions, two different thermal conditions are stimulated to the user sitting in the working environment in front of the computer (high temperature 30 °C and low temperature 20 °C). The connected camera can continuously capture images of the head and facial skin to detect bleeding subtle changes in flow, inferring the regulation mechanism of human body temperature and thermal comfort. The camera on the mobile computer can be used to easily capture the human skin. The technology parts such as the face detection, skin pixels isolation, image magnification and the detection index calculation can extract human body thermal comfort information contained in the video. In the recognition process, it is necessary to eliminate the influence of irrelevant areas such as facial eyebrows and beard. It is also necessary to consider the possible interference of different lighting on the performance of the method (the original image should be subtracted from the enlarged image to consider the variable original color intensity) and eliminate the brightness channel to reduce the impact of various lighting. The feasibility evaluation of this scheme was carried out. Twenty-one participants were stimulated under different ambient temperatures of a low temperature (20 °C) and a high temperature (30 °C). Of the 18 statistically significant cases, a total of 16 cases were observed using the optimal method combination, with a success rate of 89%. The results showed that it is feasible to use the human body temperature regulation mechanism (blood perfusion change) and the Euler video amplification algorithm to infer thermal comfort state through RGB video images under different ambient temperatures. Building occupants (especially office/administration buildings) can use this non-invasive platform to interact with personal computers using commonly connected video devices, which is not only expected to achieve non-invasive, real-time, personalized thermal comfort measurement, but also provide feedback signals for energy management. However, the above experiments require the human subjects to remain still while recording to minimize changes in light and movement, which is unavoidable in practical applications. Subsequently, a framework for extracting subtle changes in photoplethysmography (PPG) signals using facial RGB video images recorded from a distance was proposed[69]. After separating the region of interest (cheek), the combination of independent component analysis and least mean squares (LMS) adaptive filtering algorithms are integrated into a framework, and the effects of unwanted and in-band artifacts can be eliminated while retaining the amplitude information of the PPG signal. In addition, the feasibility of using the Doppler radar sensing (DRS) system to express passenger thermal comfort with changes in breathing intensity has also been studied[70]. Results illustrated that the real-time measurement of respiration can be used as an index of occupants' thermoregulation state to achieve smart control of the building HVAC system.

4.3. Skeleton keypoints model aided normal camera

Human pose estimation has been explored for many years [49] and it was widely used in different fields, such as video games, robotics[59]and medical science[14]. Body parts, such as the torso, limb, face and finger were captured [31]. A generic convolution neural network can be applied to the human pose estimation. [13]. To capture human poses more accurately, skeleton keypoints were also proposed[54,77,62] . The skeletal node model has good dynamic capture, remote location of personnel information, wide application range, and strong system adaptability. The task of pose estimation was completed by convolutional pose machines through learning image features and image-dependent spatial models[60]. An open source software which named Openpose was also released, which can be applied to real-time single or multiple human pose estimation[58]. In addition to the Euler video magnification technology, the skeleton keypoints model can also assist normal camera to assess human thermal comfort in a non-contact way. Thermal comfort can not only be reflected in specific physiological parameters but also be expressed in human poses.

Kinect for detecting thermal comfort/discomfort related postures was proposed[11]. Four types of postures were defined, and the logical relationship between posture and thermal discomfort was established. Database of "heat discomfort postures" needs to be established. In addition, Kinect was applied to detect metabolic rates by adopting image classifications using the deep learning algorithm[33]. However, practical application of Kinect is not scalable and economical. As a special device generally used for computer games, Kinect is protected by patents. As a solution, open source platforms (e.g., Openpose) can be used to generate coordinates of human skeleton keypoints. Twelve thermal discomfort poses were defined, including: "sweat", "hand fan wind", "shake T-shirt", "scratch", "roll up sleeves", "walk", "shake" "shoulders", "crossed arms", "crossed legs", "necks with both hands", "warm hands with breath" and "stomp"[16]. The poses were compared with questionnaire survey results. Compared with the infrared camera mentioned earlier, the initial investment is reduced and no additional costs are required. Mobile phone or computer camera can be used for data collection.

Unlike the Euler video magnification technology, which is now targeted at stationary people, the skeletal keypoints model can also pick up and identify human skeleton keypoints with high accuracy when human body moves. The technology can also have the feasibility of remote measurements[16]. However, the wrong judgment of human comfort/discomfort may be occurred based on the poses. Cross-validation of the same poses from different occupants is necessary.

However, there are still technical limitations in the accuracy of predicting activity levels and metabolic rates [33]. Due to individuals' physiological differences, a developed prediction model's performance has frequently been not consistent, depending on gender and physical shapes. For example, a similar action intensity could be applied to individuals differently, and a predicted metabolic rate could be variously perceived per individual in practice. In addition, a specific angle is usually pre-defined to capture a preferred image for the models. People may not show the presumptive poses when feeling hot or cold. Poses, defined in the thermal discomfort library, may be caused by other reasons non-related to hot/cold discomfort. For an instance, stamping feet may not be caused by cold discomfort but dirty shoes. These technical drawbacks limit the application of skeleton keypoint-based image models to reality.

5. Discussion

5.1. Non-contact measurements for personalized thermal comfort

Infrared imaging technology is rapidly evolving in both built environment research and industrial fields over the past 5 decades. It is widely considered as an excellent non-contact inspection tool for monitoring and diagnosing building conditions. Infrared images could visually display the surface temperature of buildings, which is affected by the heat flow, air and moisture through the building envelope. These three factors not only affect building durability and energy efficiency but also occupant comfort, health and safety.

It has been well known that it is not possible to satisfy all occupants with the same indoor condition due to large individual differences. To achieve individual thermal comfort, individual thermal status must be analyzed and simultaneously being sent to the process control of personal comfort systems to trigger proper actions to meet individual needs. Infrared imaging technology is recognized as one of the most convenient approaches to measure real time skin temperature of occupants. This technology has been proposed as a potential personal based energy efficiency control strategy to improve individual occupant thermal comfort. It should be mentioned that such control strategy is mainly based on room level. With the rapid development and technology advancing on personal thermal management systems, the application of infrared imaging technology to control a personal thermal management system such as personal cooling or warming clothing seems promising. The concept is believed to further enhance individual occupant thermal comfort as well as save enormous built conditioning energy.

Nevertheless, the infrared imaging technology has inherent limitations. First, infrared imaging technology could only measure naked skin temperatures but not the temperature of local body sites that are covered by clothing or deep body temperatures. To measure the temperature of clothed body part, occupants have to stop the normal activity and take off the clothing. Hence, this procedure has no longer been defined as non-invasive. Therefore, only the temperatures are the facial area, hands or lower arms may be conveniently measured by the infrared imaging technology. In spite of local skin temperatures at these sites are useful for predicting thermal and comfort sensations, these areas account for a very small portion of the entire skin surface, and thereby, accurately prediction of overall thermal comfort or local thermal comfort at other clothed body parts is challenging. Second, the infrared camera has a relatively low measurement accuracy compared to thermistors. Most existing infrared cameras have a measurement accuracy of ± 2 K or ± 2% of measured temperature, which could greatly decrease the judgement of time dependent individual thermal status. Besides, high definition cameras are pricy. Third, the quality of infrared images is influenced by many factors such as test conditions, view angle, emissivity, stabilization time and background radiation sources. Thus, more research is needed to determine the adequate procedures for image acquisition and analysis. There is also a need to train the experimenter to help control different influential factors that could affect the measurement accuracy.

5.2. Non-contact measurements for demand-oriented environmental controls

Skeleton keypoints model, as one of the video/image based non-contact methods, was used not only to recognize occupants' thermal comfort/discomfort poses but also to positioning indoor occupants and estimate poses. Video/image based non-contact methods overcome the limitations of traditional occupants counting and positioning methods such as temperature and CO_2 sensor based method, passive infrared ray (PIR) sensor based method, radio frequency identification (RFID) based method, Bluetooth low energy (BLE) based method, and so forth.

Zonal occupant counting can be obtained accurately by the video/image based non-contact occupant positioning[47]. Recognition algorithm, based on the convolutional neural network, can achieve a detection rate of 95.2% for human head-shoulder targets [42]. Multiple vision sensors, aided by the Bayesian algorithm data fusion, can improve sensing accuracy [22]. Above mentioned studies were mainly focused on occupants' positioning, without obtaining human poses which reflected operating modes of multi-functional rooms. Skeleton keypoints model was developed for occupants' positioning and pose recognition. The method can be used for detecting operating modes of multi-functional rooms (classroom/conference room) and controlling the demand-based HVAC system [34]. Image collection, extraction, 3D reconstruction and data fusion can be finished in 1.5 s for achieving real time human positioning and pose recognition.

The speed of image/video data collection, extraction, analysis and signal transmission is faster than the operation speed of mechanical devices (damper, valve, VSD fan, etc.) in demand based HVAC systems. Mismatch or even wrong adjustment may happen, which impeded the practical applications of demand based HVAC technologies and image/video based non-contact sensing technologies. Performance improvement of corresponding mechanical devices is necessary. New technologies were tried, such as energy efficient fans working together with less intensified air conditioning system. Room temperature setpoint is unchanged, which avoids the limitation of slow adjustment speed of the air conditioning system. Quick adjustment of energy efficient fan speed can be achieved, which is matched with the speed of image/video based non-contact sensing technologies. Room size, room irregular shape, mutual blockage among occupants are also the important influential factors for the image/video based non-contact sensing technologies.

Considering the too cold thermal condition in commercial office buildings, frequently witnessed during the cooling season, an optimal setpoint temperature provides an opportunity to enhance energy efficiency. The collected image/video data and information provide a reasonable accuracy to estimate individual building occupants. Based on the composite information of individual users, an optimally estimated set point temperature could be overridden depending on the occupants' physiological conditions and status with the consideration of seasonal, monthly, and daily effects. For example, a higher setpoint temperature has potential to contribute to 1 to 1.5% cooling energy saving per degree change, and vice versa for heating conditions.

6. Conclusions

Rapid developments of new technologies in computer vision, image/video processing, infrared imaging fields promote measuring and sensing methods from contact manner to non-contact manner. Main achievements and future directions are summarized as follows.

1. Low cost and miniaturized thermal camera, with uncooled infrared detectors, were integrated into smartphone. Cooled infrared detectors can be further miniaturized in the future. More intelligent correction method will be developed to improve accuracy of thermal image.
2. Euler video magnification technology was used to detect the skin temperature variation from weak thermal stimulus to strong thermal stimulus. Image/video processing technologies were improved to isolate unwanted skin regions, improve accuracy and avoid influences from human movements.
3. Skeleton keypoints model was applied to test human thermal discomfort/comfort poses, a library of which was established. Cross validation methods should be developed to test whether poses in the library are really correlated to certain thermal discomfort. More occupants with one same thermal discomfort pose and one occupant with more thermal discomfort poses can be used to validate the correction. The technology can also be used for sending feedback signals to control the demand based HVAC.

Overall, this review paper has a large potential to guide future study directions with consideration of the current research outcomes and their technical merits and limitations. It also confirms the research parameters to investigate further in the Building Technology domain. However, Due to restricted access to the detailed data of individual case studies selected in this review, comprehensive assessment was not be able to conduct, especially on detailed technical features, such as the sensing frequency, generated signal noise and filtration strategies, and potential compatibility to existing building systems, etc. Therefore, additional review research should be conducted to investigate specified computational and sensing processes, and effective data acquisition methods, as well as thermal perception estimation per individual and general occupants with the consideration of practical functional merits in terms of cost, usability, and practicality.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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