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



## Authors
Yang, Bin
Li, Xiaojing
Hou, Yingzhen
et al.

## Publication Date
2020-10-01

## DOI
10.1016/j.enbuild.2020.110261

Peer reviewed

Yang, Bin, Xiaojing Li, Yingzhen Hou, Alan Meier, Xiaogang Cheng, Joon-Ho Choi, Faming Wang, et al. "Non-Invasive (Non-Contact) Measurements of Human Thermal Physiology Signals and Thermal Comfort/Discomfort Poses -A Review." *Energy and Buildings* 224 (October 1, 2020): 110261. https://doi.org/10.1016/j.enbuild.2020.110261.

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

Bin Yang[1,2,*] , Xiaojing Li[1], Yingzhen Hou[1], Alan Meier[3,4], Xiaogang Cheng[2,5], Joon-Ho Choi[6], Andreas Wagner[7], Da Yan[8], Angui Li[1,2], Thomas Olofsson[2], Haibo Li[9]

[1]School of Building Services Science and Engineering, Xi'an University of Architecture and Technology, Xi'an, 710055, China

[2]Department of Applied Physics and Electronics, Umeå University, Umeå, 90187, Sweden

[3]Energy and Efficiency Institute, University of California, Davis, CA, 95616, USA

[4]Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, CA, 94720, USA

[5]College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing, 210003, China

[6]School of Architecture, University of Southern California, CA, 90089, USA

[7]Institute for Building Design and Technology, Karlsruhe Institute of Technology, Karlsruhe, 76131, Germany

[8]Department of Building Science, School of Architecture, Tsinghua University, Beijing, 100084, China

[9]School of Electrical Engineering and Computer Science, Royal Institute of Technology, Stockholm, 10044, Sweden

[*]*Corresponding email: yangbin@xauat.edu.cn (B. Yang)*

## Abstract

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 systems 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 incorporate 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. However, with the help of advanced technologies, physiological signals have been read, measured and processed by using multiple technical formats, such as wearable sensors, but they mostly require physical contacts to the skins in spite of the small physical dimension and compatibility to other wearable accessories, such as glasses, intelligent bracelet, etc. Most recently, a low cost small infrared camera has been adopted to monitor human facial images, which could detect facial skin temperature and blood perfusion in a non-contact 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, the summary of the new sensing technologies were given, and these cons and pros were discussed and extended applications for demand-oriented ventilation and animal monitoring were also reviewed as potential development and applications.

*Keywords:* non-invasive (non-contact) measurements; thermal physiology signals; thermal comfort/discomfort poses; Euler video magnification; skeleton keypoints

## 1. **Introduction**

Building energy supply and indoor environmental conditioning should be performed in demand base and intelligent manner. Nowadays, building centered design was changed to human centered design. Terminology, such as human building integration, was frequently mentioned. Traditional methods of controlling thermal environments rely on research performed on 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. Questionnaire survey based 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. Traditional invasive measurements are reviewed in section 3. Semi and mini invasive measurements are reviewed in section 4. Non-invasive measurements, including infrared camera technology, Euler video magnification technology; skeleton keypoints technology, are reviewed in section 5. Extension applications of infrared camera technology for animals and skeleton keypoints technology for 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.

Before the review content, the tiny difference between non-invasive and non-contact should be clarified. A medical procedure is defined as non-invasive when no break in the skin is created and there is no contact with the mucosa, or skin break, or internal body cavity beyond a natural or artificial body orifice. For centuries, physicians have employed many simple non-invasive methods based on physical parameters in order to assess body function in health and disease (physical examination and inspection), such as pulse-taking, the auscultation of heart sounds and lung sounds (using the stethoscope), temperature examination (using thermometers), respiratory examination, peripheral vascular examination, oral examination, abdominal examination, external percussion and palpation, blood pressure measurement (using the sphygmomanometer), change in body volumes (using plethysmograph), audiometry, eye examination, and many others (Wikipedia, 2020). Based on above-mentioned definition, the term "non-contact" is more precise although the term "non-invasive" was more commonly used in the literature.

## 2. Traditional invasive measurements

Traditional invasive measurements include surveys, physiological measurements and environmental measurements. A survey, typically in the form of questionnaire, is the most direct method because it extract occupants' state of mind to thermal environments. Surveys are invasive because they require the occupants to 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 (Zagreus et al., 2004) and cell phone based apps can be used but need continuous and frequent user feedback (Sanguinetti et al., 2017). 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. Location difference between environmental sensors and occupants, non-uniform distribution of air temperature, speed and solar radiation, are main challenges (Ghahramni et al., 2015; Ghahramni et al., 2016).

Physiological measurement can be correlated with thermal comfort/discomfort (Huizenga et al., 2004; Takada et al., 2013; Choi et al., 2017). 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 (Chen et al., 2015). Foreign body sensation is the main obstacle for practical measurements.

## 3. **Semi and mini-invasive measurements**

Instead of traditional invasive methods with body contact physically, semi and mini invasive methods were presented by integrating sensors to human wore accessories. Four infrared sensors were integrated to eyeglasses to extract skin temperature from the front face, cheekbone, nose and ear for thermal comfort assessment and thermal regulation performance analysis (Ghahramni et al., 2016). Based on the results, a hidden Markov model based learning method was developed (Ghahramni et al., 2018).

Wrist-type wearable devices, such as smart bracelet, can be used to measure wrist skin temperature (Empatica, 2019; Microsoft, 2019). Skin temperatures from three different wrist parts were monitored for sedentary occupants under different room temperatures, together with fingertip skin temperature measurements (Sim et al., 2016). Accordingly, 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 (Nkurikiyeyezu and Lopez, 2018). The wristband was also used to dynamically correct offset errors for thermal images captured by smartphone thermal cameras (Yoshikawa et al., 2019). Measuring results of skin temperature and heart rate (HR)/heart rate variability (HRV) from smartwatch were used to develop thermal sensation estimation models (Li et al., 2018; Li et al., 2019). They were also compared with results from professional measuring devices (Kobiela et al., 2019).

## 4. **Non-invasive measurements**

Traditional invasive measurements, including a questionnaire survey, monitoring of environmental parameters and human physiological parameters were widely used and integrated with Internet of Things (IoT), Artificial Intelligence (AI) and machine learning. Minimized measuring sensors are more user-friendly to be accepted. Sensors were also integrated into human wore accessories, such as glasses, watches, to avoid foreign body sensation.

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

### *4.1 Infrared camera technology*

Before being used for thermal comfort assessment, videos and images captured by infrared camera were widely used for emotion and expression recognition (Puri et al., 2005; Trujillo et al., 2005; Salazar-López et al., 2015; Basu et al., 2015), medical detection (Bouzida et al., 2009; Cho and Yoon, 2014; Pauk et al., 2019), face recognition and landmarking (Çeliktutan et al., 2013; Farokhi et al., 2016; Bayram and Bolat, 2018; Kumar and Garg, 2019), lie detection (Pavlidis and Levine, 2002; Zhu et al., 2007; Ioannou et al., 2014), and so forth.

Infrared camera was widely used for collecting and analyzing infrared images of nude skin such as facial, hand skin (Bouzida et al., 2009; Burzo et al., 2014; Ranjan and Scott; 2016; Burzo et al., 2017; Pavlin et al., 2017; Wang et al., 2017; Li et al., 2018; Metzmacher et al., 2018), which could be used to control HVAC systems in energy efficient manner without influencing thermal comfort (Ranjan and Scott, 2016). 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 (Oliveira et al., 2007). Recently, low cost and miniaturized models are commercially available, such as smartphone based thermal camera (FLIR, 2019). 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 (Yoshikawa et al., 2019). Infrared camera technology was also compared with traditional invasive measurements of ambient air temperature and semi invasive measurements of wrist-type wearable devices (Aryal and Becerik-Gerber, 2019). Accuracy tradeoffs among them were analyzed. To solve the issue of occupants' relative movements to thermal camera, one 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 (Aryal and Becerik-Gerber, 2019). Combination of different algorithms, including face detection, landmark detection, face frontalization and analysis, was tried to analyze infrared face images (Kopaczka et al., 2019). Infrared camera was also used for collecting and analyzing infrared images of athletes during outdoor running and indoor treadmill running (Tanda, 2016).

Three sensors, including a thermographic camera, a depth sensor and a color camera, were integrated into one sensing platform named RGB-DT (RedGreenBlue-DepthTemperature) to extract skin and clothing temperature for thermal comfort assessment (Cosma and Simha, 2018). The sensing platform followed three principles, which are low cost (USD 300), small form-factor device and real-time capabilities. Based on the methods, machine learning method was used to do prediction and analysis (Cosma and Simha, 2019). 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 (Li et al., 2019).

### *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 (Liu et al., 2005). 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 (Wu et al., 2012). 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 (Video magnification, 2012). 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 can 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 skin color saturation and skin temperature is established (Cheng et al., 2017). A non-contact human skin temperature measurement technology that can be used as feedback signals for HVAC systems is proposed. The color of 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 minutes. After that, video wad recorded and analyzed by magnification to obtain hand back skin color saturation. Meanwhile, 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 non-contact way.

Euler video magnification technology can accurately analyze skin color saturation. When skin temperature rises, pores expand and skin becomes red. According to the Saturation-Temperature (ST) model, skin color saturation may have a linear relationship with 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 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 video amplification technology to achieve non-contact measurements of human temperature. The NIDL algorithm was proposed and cross-validation was performed using NIDL, NIPST and iButton sensors, which further evaluated the feasibility of using Euler video magnification technology (Cheng et al., 2019). 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 (Cheng et al., 2019).

Euler video magnification technology was developed from non-contact measuring 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 (Jazizadeh and Jung, 2018). 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 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 human skin. The technology parts such as face detection, skin pixels isolation, image magnification and detection index calculation can extract human body thermal comfort information contained in the video. In 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. 21 participants were stimulated under different ambient temperatures of low temperature (20 °C) and 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 human body temperature regulation mechanism (blood perfusion change) and 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 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 (Jung and Jazizadeh, 2018). After separating the region of interest (cheek), the combination of independent component analysis and least mean squares (LMS) adaptive filtering algorithms is 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 (Jung and Jazizadeh, 2017).

### *4.3 Skeleton keypoints model aided normal camera*

Human pose estimation was explored for many years (Andriluka et al., 2009) and it was widely used in different fields, such as video games, robotics (Vemulapalli et al., 2014) and medical science (Galna et al., 2014). Body parts, such as torso, limb, face and finger were captured (Joo et al., 2018). A generic convolution neural network can be applied to the human pose estimation. (Toshev et al., 2014). To capture human poses more accurately, skeleton keypoints were also proposed (Munaro et al., 2014; Cao et al., 2017; Ghidoniand and Munaro, 2017). 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 (Wei et al., 2016). An open source software which named Openpose was also released, which can be applied to real-time single or multiple human pose estimation (Openpose, 2016). In addition to Euler video magnification technology, skeleton keypoints model can also assist normal camera to assess human thermal comfort in 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 (Meier et al., 2017). 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 also applied to detect metabolic rates by adopting image classifications using the deep learning algorithm (Na et al., 2019). 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 platform (Openpose) can be used to generate coordinates of human skeleton keypoints. Twelve thermal discomfort poses was 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" (Yang et al., 2019). The poses were compared with questionnaire survey results. Compared with 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 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 (Yang et al., 2019). However, the wrong judgement of human comfort/discomfort may be occurred based on the poses. Cross-validation of the same poses from different occupants is necessary.

## 5. Discussion

### *5.1 Non-invasive measurements for animals*

Infrared imaging technology was also used to identify thermal state of animals, which is a common measuring method in veterinary medicine, biology and other related fields. Surface temperature of animals can be easily detected to analyze and justify physiological responses of various animals.

Application of wireless remote sensing technology to monitor surface temperature of animals was firstly proposed (Bligh and Heal, 1974). Following studies demonstrated that animal body temperature can be used as an important reference value for judging health status, diagnosing diseases, breeding, and so forth (Zhang et al., 2019). Compared with non-contact measurements, traditional contact, implant and wireless sensor network temperature measurement methods caused uncontrollable and irreversible effects on normal activities and physical health of animals (Godyn and Herbu, 2017). Body temperature of different livestock and poultry were measured by non-invasive infrared imaging methods. Infrared temperature measurement technology is the main means of measuring pig body surface temperature with its advantages of non-contact, long distance and real-time (Zhang et al., 2019). Temperatures of horse's armpit, croup, breast and groin were collected by infrared images and analyzed by machine learning to predict horse thermal comfort (Maia et al., 2012). Non-contact infrared measurements were also used to diagnose lame horses and evaluate the degree of inflammation for proposing the best treatment plan (Yanmaz et al., 2007). In biological science community, it is also possible to obtain some thermal information of animals by non-invasive methods which are beneficial to the observation and understanding of thermal regulation process of different types of animals (Tattersall and Cadena, 2010). Measuring results by infrared thermal imaging technology, combined with individual animal behavior and physiological measurements, can reveal animal thermal adaptation.

Different from human beings, animals can not actively and accurately express their minds to surrounding environments. Sensor based contact measurement may cause animals stressed. Non-contact measurements of animal body surface temperature are necessary.

### *5.2 Non-invasive measurements for demand oriented ventilation*

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 video/image based non-contact occupant positioning (Walmsley-Eyre, 2017). Recognition algorithm, based on convolutional neural network, can achieve a detection rate of 95.2% for human head-shoulder targets (Zou et al., 2017). Multiple vision sensors, aided by Bayesian algorithm data fusion, can improve sensing accuracy (Liu et al., 2013). 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 demand based ventilation system (Wang et al., 2019). 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 operation speed of mechanical devices (damper, valve, VSD fan, etc.) in demand based HVAC systems. Mismatch or even wrong adjustment may happened, 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 air conditioning system. Quick adjustment of energy efficient fan speed can be achieved, which is match to the speed of image/video based non-contact sensing technologies. Room size, room irregular shape, mutual blockage among occupants are also influential factors for the image/video based non-contact sensing technologies.

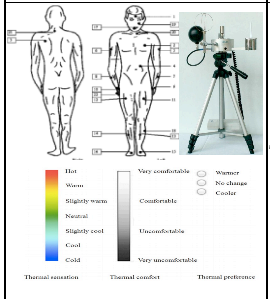
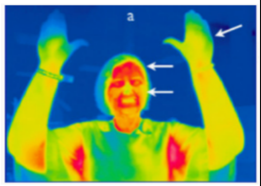
## 6. Conclusions

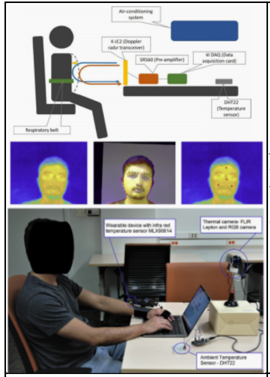
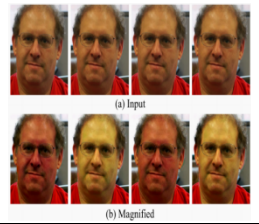
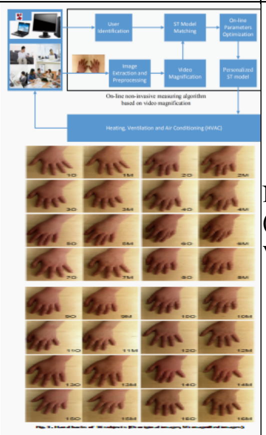
Rapid developments of new technologies in computer vision, image/video processing, infrared imaging fields promote measuring and sensing methods from contact manner to non-contact manner. Main achievements and future directions are summarized as follows.

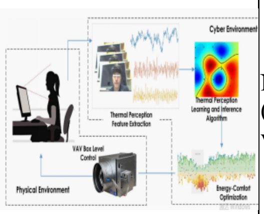
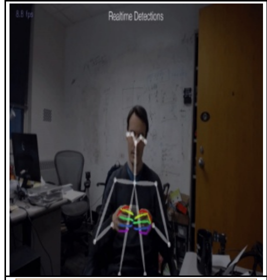
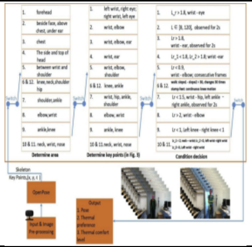
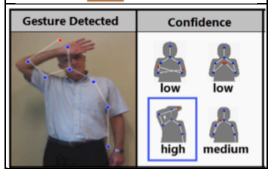
1. Low cost and miniaturized thermal camera, with uncooled infrared detectors, was integrated into smartphone. Cooled infrared detectors can be further miniaturized in the future. More intelligent correction method will be developed to improve accuracy of thermal image.
2. Euler video magnification technology was used to test 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 validate the correction. The technology can also be used for sending feedback signals to control demand based ventilation.

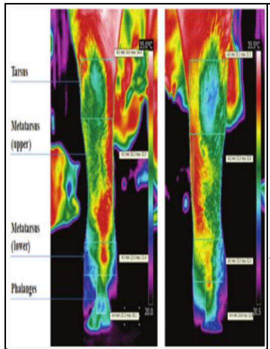
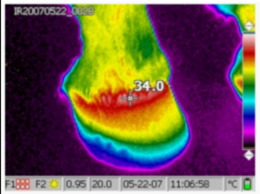
Overall, this review paper has a large potential to suggest future study directions with consideration of the current research outcomes and their technical merits and limitations. It also confirms the research parameters to investigate further in the Building Technology domain. However, Due to restricted 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 sensing frequency, generated signal noise and filtration strategies, 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.

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

| Cases | Methods | Main Contributions | Limitations | Selected References |
|---|---|---|---|---|
|  | Traditional invasive measurements | 1. Questionnaire survey, environmental parameter measurement and physiological parameter measurement were used to evaluate human thermal comfort. | 1. Continuous and frequent feedback is needed for questionnaire survey.<br>2. Environmental parameters are not direct feedback or physiological signals from human occupants.<br>3. Foreign body sensation is the main obstacle for physiological parameter measurement. | Huizenga et al., 2004<br>Zagreus et al., 2004<br>Takada et al., 2013<br>Chen et al., 2015<br>Ghahramni et al., 2015<br>Ghahramni et al., 2016 |
|  | Semi and mini-invasive measurements | 1. Integrating infrared sensor to glasses to measure human physiological parameters, a semi-invasive human thermal comfort measurement scheme was proposed.<br>2. Wrist-type wearable devices, such as smart bracelet, can be used to measure wrist skin temperature, pulse rate variability, etc. | 1.Not all people wear glasses and wrist-type wearable devices.<br>2.The sense of foreign body is weakened but not eliminated.<br>3. The allowed ambient thermal ranges are limited for accurate sensing. | Ghahramni et al., 2016<br>Sim et al., 2016<br>Ghahramni et al., 2018<br>Nkurikiyeyezu and Lopez, 2018<br>Choi et al, 2019<br>Li et al., 2019 |
|  | Non-invasive 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. | Infrared cameras are usually high cost and big size. | Oliveira et al., 2007<br>Bouzida et al., 2009<br>Burzo et al., 2014;<br>Ranjan and Scott; 2016<br>Burzo et al., 2017<br>Pavlin et al., 2017<br>Wang et al., 2017<br>Li et al., 2018<br>Metzmacher et al., 2018<br>Yoshikawa et al., 2019 |

| | | | | |
|---|---|---|---|---|
|  | Non-invasive 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. | | Cosma and Simha, 2018<br>Aryal and Becerik-Gerber，2019<br>Cosma and Simha, 2019<br>Li et al., 2019 |
|  | Euler video magnification | 1. 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.<br>2. 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. | | Liu et al., 2005<br>Wu et al., 2012 |
|  | Non-invasive measurements (ordinary camera combined with Euler video magnification) | 1. Euler video magnification was firstly used to monitor human thermal comfort and control HVAC system.<br>2. A preliminary experiment of non-contact measurement was carried out under the condition of weak stimulation of human hand in 45 °C warm water.<br>3. The skin image was trained by using big data and the NIDL algorithm.<br>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.<br>2.The experiment was only performed under strong stimulation conditions | Cheng et al., 2017<br>Cheng et al., 2019 |

| | | | | |
|---|---|---|---|---|
|  | Non-invasive measurements (ordinary camera combined with Euler video magnification) | 1. 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.<br>2. The video post-processing technology was explored to eliminate the influence of interference areas and artifacts. | 1. The influence of human movement and background light is unavoidable. | Jung and Jazizadeh, 2017<br>Jazizadeh and Jung, 2018<br>Jung and Jazizadeh, 2018 |
|  | Skeleton keypoints model | 1. Dynamic poses can be captured in real time.<br>2. Multi-person and single-person pose estimation based on deep learning was proposed.<br>3. It was widely used in different fields, such as video games, robotics, medical science, etc. | | Munaro et al., 2014<br>Cao et al., 2017;<br>Ghidoniand and Munaro, 2017 |
|  | Non-invasive measurements method (Skeleton keypoints mode) | 1. The twelve poses of thermal discomfort was defined.<br>2. An algorithm was proposed to associate thermal uncomfortable poses with thermal uncomfortable feeling. | 1. 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. | Yang et al., 2019 |
|  | | 1. Four thermal discomfort related poses were defined.<br>2. Library of thermal discomfort poses was established. | The Kinect is protected by many patents and its application scope is limited. | Meier et al., 2019 |

| | | | | |
|---|---|---|---|---|
|  | Application of non-invasive measurements for animals | 1. The method has no stress on animals and is consistent with the concept of welfare agriculture and provides less labor.<br>2. This method can improve temperature measurement efficiency.<br>3. Infrared temperature measurement can be monitored in real time and remotely. | 1. Measurement technology and data processing technology need to be optimized. | Zhang et al., 2019 |
|  | | 1. Dynamic posture can be captured in real time.<br>2. Multi-objects pose estimation based on deep learning was proposed. | 1. Measurement technology and data processing technology need to be optimized. | Yanmaz et al., 2007<br>Tattersall et al., 2010<br>Maia et al., 2012 |
|  | Application of non-invasive measurements in demand oriented ventilation | 1. A new image based indoor personnel positioning and pose recognition system was set up.<br>2. The method can be used for detecting operating modes of multi-functional rooms (classroom/conference room) and controlling demand oriented ventilation systems. | 1. 3D reconstruction accuracy need to be improved. | Wang et al., 2019 |

## References

A. Aryal, B. Becerik-Gerber, A comparative study of predicting individual thermal sensation and satisfaction using wrist-worn temperature sensor, thermal camera and ambient temperature sensor, *Build. Environ.* 160 (2019) 106223.

A. Aryal, B. Becerik-Gerber, Skin temperature extraction using facial landmark detection and thermal imaging for comfort assessment, In Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '19), New York, NY, USA, 13–14 November 2019, 71–80.

A. Basu, A. Routray, S. Shit, S.; A. K. Deb, Human emotion recognition from facial thermal image based on fused statistical feature and multi-class SVM, In Proceedings of the 2015 Annual IEEE India Conference (INDICON), New Delhi, India, 17–19 December 2015, 1–5.

A. C. Cosma, R. Simha, Machine learning method for real-time non-invasive prediction of individual thermal preference in transient conditions, *Build. Environ.* 148 (2019) 372–383.

A. C. Cosma, R. Simha, Thermal comfort modeling in transient conditions using real-time local body temperature extraction with a thermographic camera, *Build. Environ.* 143 (2018) 36–47.

A. Ghahramani, C. Tang, B. Becerik-Gerber, An online learning approach for quantifying personalized thermal comfort via adaptive stochastic modeling, *Build. Environ.* 92 (2015) 86–96.

A. Ghahramani, G. Castro, B. Becerik-Gerber, X. Yu, Infrared thermography of human face for monitoring thermoregulation performance and estimating personal thermal comfort, *Build. Environ.* 109 (2016) 1–11.

A. Ghahramani, G. Castro, S. A. Karvigh, B. Becerik-Gerber, Towards unsupervised learning of thermal comfort using infrared thermography, *Appl. Energ.* 211 (2018) 41–49.

A. Meier, W. Dyer, C. Graham, Using human gestures to control a building's heating and cooling system, In Proceedings of the 9th International Conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL), Irvine, California, USA, 13–15 September 2017, 627–635.

A. P. A. Maia, S. R. M. Oliveira, D. J. Moura, J. Sarubbi, R. A. Vercellino, B. B. L. Medeiros, P. R. Griska, A decision-tree-based model for evaluating the thermal comfort of horses, *Sci. Agric.* 70 (2013) 377–383.

A. Sanguinetti, M. Pritoni, K. Salmon, A. Meier, J. Morejohn, Upscaling participatory thermal sensing: Lessons from an interdisciplinary case study at University of California for improving campus efficiency and comfort, *Energ Res. Soc. Sci.* 32 (2017) 44–54.

A. Toshev, C. Szegedy, Deeppose: Human pose estimation via deep neural networks, In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA , 23–28 June 2014, 1653–1660.

B. Galna, G. Barry, D. Jackson, D. Mhiripiri, P. Olivier, L. Rochester, Accuracy of the Microsoft Kinect sensor for measuring movement in people with Parkinson's disease, *Gait Posture* 39 (2014) 1062–1068.

B. Pavlin, G. Pernigotto, F. Cappelletti, P. Bison, R. Vidoni, A. Gasparella, Real-time monitoring of occupants' thermal comfort through infrared imaging: A preliminary study, *Buildings* 7 (2017) 10.

B. Yang, X. Cheng, D. Dai, T. Olofsson, H. Li, A. Meier, Real-time and contactless measurements of thermal discomfort based on human poses for energy efficient control of buildings, *Build. Environ.* 162 (2019) 106284.

C. Huizenga, H. Zhang, E. Arens, D. Wang, Skin and core temperature response to partial- and whole-body heating and cooling, *J. Therm. Biol.* 29 (2004) 549–558.

C. Liu, A. Torralba, W. T. Freeman, F. Durand, E. H. Adelson, Motion magnification, *ACM Trans. Graph.* 24 (2005) 519–526.
C. Puri, L. Olson, I. Pavlidis, J. Levine, J. Starren, StressCam: Non-contact measurement of users' emotional states through thermal imaging, In Proceedings of the CHI '05 Extended Abstracts on Human Factors in Computing Systems, New York, NY, USA, 2–7 April 2005, 1725–1728.
D. Li, C. C. Menassa, V. R. Kamat, Non-intrusive interpretation of human thermal comfort through analysis of facial infrared thermography, *Energ. Build.* 176 (2018) 246–261.
D. Li, C. C. Menassa, V. R. Kamat, Robust non-intrusive interpretation of occupant thermal comfort in built environments with low-cost networked thermal cameras, *Appl. Energ.* 251 (2019) 113336.
D. Liu, X. Guan, Y. Du, Q. Zhao, Measuring indoor occupancy in intelligent buildings using the fusion of vision sensors, *Meas. Sci. Technol.* 24 (2013) 074023.
Empatica. Real-Time Physiological Signals | E4 EDA/GSR Sensor. Available online: https://www.empatica.com/en-int/research/e4/
E. Salazar-López, E. Domínguez, V. J. Ramos, J. de la Fuente, A. Meins, O. Iborra, G. Gálvez, M. A. Rodríguez-Artacho, E. Gómez-Milán, The mental and subjective skin: Emotion, empathy, feelings and thermography, *Conscious. Cogn.* 34 (2015) 149–162.
F. D. Oliveira, S. Moreau, C. Gehin, A. Dittmar, Infrared imaging analysis for thermal comfort assessment, In Proceedings of the 29th Annual International Conference of the IEEE EMBS Cité Internationale, Lyon, France, 23–26 August 2007, 3373–3376.
F. Jazizadeh, W. Jung, Personalized thermal comfort inference using RGB video images for distributed HVAC control, *Appl. Energ.* 220 (2018) 829–841.
F. Kobiela, R. Shen, M. Schweiker, R. Dürichen, Personal thermal perception models using skin temperatures and HR/HRV features - comparison of smartwatch and professional measurement devices, In Proceedings of the 23rd International Symposium on Wearable Computers (ISWC '19), London, UK, 9–13 September, 2019, 96–105.
F. Wang, B. Zhu, R. Li, D. Han, Z. Sun, S. Moon, Z. Gong, W. Yu, Smart control of indoor thermal environment based on online learned thermal comfort model using infrared thermal imaging, In Proceedings of the 13th IEEE Conference on Automation Science and Engineering (CASE), Xi'an, China, 20–23 August 2017, 924–925.
FLIR. FLIR ONE Pro | FLIR Systems. Available online: https://www.flflir.com/products/flflir-one-pro/
G. J. Tattersall, V. Cadena, Insights into animal temperature adaptations revealed through thermal imaging, *Imaging Sci. J.* 58 (2013) 261–268.
G. Tanda, Skin temperature measurements by infrared thermography during running exercise, *Exp. Therm. Fluid. Sci.* 71 (2016) 103–113.
H. Joo, T. Simon, Y. Sheikh, Total capture: A 3d deformation model for tracking faces, hands, and bodies, In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA , 18–23 June 2018, 8320–8329.
H. Metzmacher, D. Wölki, C. Schmidt, J. Frisch, C. Treeck, Real-time human skin temperature analysis using thermal image recognition for thermal comfort assessment, *Energ. Build.* 158 (2018) 1063–1078.
H. Na, J. H. Choi, H. Kim, T. Kim, Development of a human metabolic rate prediction model based on the use of Kinect-camera generated visual data-driven approaches, *Build. Environ.* 160 (2019) 106216.
H. Wang, J. Wang, X. Li, Image based positioning system for indoor occupants, *Build. Environ. Energ. (Chinese Journal)* 28 (2019) 170–174.

H. Yoshikawa, A. Uchiyama, T. Higashini, ThermalWrist: Smartphone thermal camera correction using a wristband sensor, *Sensors* 19 (2019) 3826.
H-Y. Wu, M. Rubinstein, E. Shih, J. V. Guttag, F. Durand, W. T. Freeman, Eulerian video magnification for revealing subtle changes in the world, *ACM Trans. Graph* 31 (2012) 1–8.
I. Pavlidis, J. Levine, Thermal image analysis for polygraph testing, *IEEE Pulse* 21 (2002) 56–64.
J. Bligh, J. W. Heal, The use of radio-telemetry in the study of animal physiology, *Proc. Nutr. Soc.* 33 (1974) 173–181.
J. H. Choi, D. Yeom, Development of the data-driven thermal satisfaction prediction model as a function of human physiological responses in a built environment, *Build. Environ.* 150 (2019) 206–218.
J. H. Choi, D. Yeom, Study of data-driven thermal sensation prediction model as a function of local body skin temperatures in a built environment, *Build. Environ.* 121 (2017) 130–147.
J. Pauk, A. Wasilewska, M. Ihnatouski, Infrared thermography sensor for disease activity detection in rheumatoid arthritis patients, *Sensors* 19 (2019) 3444.
J. Ranjan, J. Scott, ThermalSense: Determining dynamic thermal comfort preferences using thermographic imaging, In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Heidelberg, Germany, 14–16 September 2016 1212–1222.
J. Zou, Q. Zhao, W. Yang, F. Wang, Occupancy detection in the office by analyzing surveillance videos and its application to building energy conservation, *Energ. Build.* 152 (2017) 385–398.
K. Nkurikiyeyezu, G. Lopez, Towards a real-time and physiologically controlled thermal comfort provision in office buildings, *Intell. Enviro.* 23 (2018) 168–177.
K. S. Bayram, B. Bolat, Multibiometric identifification by using ear, face, and thermal face, *EURASIP J. Image Video Process.* (2018) 32.
K. S. Cho, J. Yoon, Fever screening and detection of febrile arrivals at an international airport in Korea: Association among self-reported fever, infrared thermal camera scanning, and tympanic temperature, *Epidemiol. Health* 36 (2014) e2014004.
L. E. Yanmaz, A. Okumus, E. Dogan, Instrumentation of thermography and its application in horses, *J. Anim. Vet. Adv.* 6 (2007) 858–862.
L. Trujillo, G. Olague, R. Hammoud, B. Hernandez, Automatic feature localization in thermal images for facial expression recognition, In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)-Workshops, San Diego, CA, USA, 21–23 September 2005, 1–14.
L. Walmsley-Eyre, R. Cardell-Oliver, Hierarchical classification of low resolution thermal images for occupancy estimation, In Proceedings of the IEEE 42nd Conference on Local Computer Networks Workshops (LCN Workshops), Singapore, 9 October 2017, 9–17.
L. Zagreus, C. Huizenga, E. Arens, D. Lehrer, Listening to the occupants: a Web-based indoor environmental quality survey, *Indoor Air* 14 (2004) 65–74.
M. Andriluka, S. Roth, B. Schiele, Pictorial structures revisited: People detection and articulated pose estimation, In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, USA, 20–25 June 2009, 1014–1021.
Microsoft. Microsoft Band | Offficial Site. Available online: https://support.microsoft.com/ja-jp/help/4000313/band-hardware-band-2-features-and functions
M. Burzo, M. Abouelenien, V. Pérez-Rosas, C. Wicaksono, Y. Tao, R. Mihalcea, Using infrared thermography and biosensors to detect thermal discomfort in a building's inhabitants,

In Proceedings of the ASME 2014 International Mechanical Engineering Congress and Exposition, Montreal, Quebec, Canada, 14–20 November 2014, 1–11.
M. Burzo, M. Abouelenien, D. V. Alstine, K. Rusinek, Thermal discomfort detection using thermal imaging, In Proceedings of the ASME 2017 International Mechanical Engineering Congress and Exposition, Tampa, Florida, USA, 3–9 November 2017, 1–11.
M. Kopaczka, L. Breuer, J. Schock, D. Merhof, A modular system for detection, tracking and analysis of human faces in thermal infrared recordings, *Sensors* 19 (2019) 4135.
M. Munaro, S. Ghidoni, D. T. Dizmen, E. Menegatti, A Feature-based approach to people re-identification using skeleton keypoints, Hong Kong, China, 31 May–7 June 2014, 5644–5651.
N. Bouzida, A. Bendada, X. P. Maldague, 2009, Visualization of body thermoregulation by infrared imaging, *J. Therm. Biol.* 34 (2009) 120–126.
N. Kumar, V. Garg, Single sample face recognition in the last decade: A Survey, *Int. J. Pattern Recognit. Artif. Intell.* (2019) 1956009.
O. Çeliktutan, S. Ulukaya, B. Sankur, A comparative study of face landmarking techniques, *EURASIP J. Image Video Process.* (2013) 13.
OpenPose. https://github.com/CMU-Perceptual-Computing-Lab/openpose
R. Vemulapalli, F. Arrate, R. Chellappa, Human action recognition by representing 3d skeletons as points in a lie group, In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA , 23–28 June 2014, 588–595.
S-E. Wei, V. Ramakrishna, T. Kanade, Y. Sheikh, Convolutional pose machines, In Proceedings of The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016, 4724–4732.
S. Farokhi, J. Flusser, U.U. Sheikh, Near infrared face recognition: A literature survey, *Comput. Sci. Rev.* 21 (2016) 1–17.
S. Ghidoni, M. Munaro, A multi-viewpoint feature-based re-identification system driven by skeleton keypoints, *Robot. Auton. Syst.* 90 (2017) 45–54.
S. Ioannou, V. Gallese, A. Merla, Thermal infrared imaging in psychophysiology: Potentialities and limits, *Psychophysiology* 51 (2014) 951–963.
S. Takada, S. Matsumoto, T. Matsushita, Prediction of whole-body thermal sensation in the non-steady state based on skin temperature, *Build. Environ.* 68 (2013) 123–133.
S. Y. Sim, M. J. Koh, K. M. Joo, S. Noh, S. Park, Y. H. Kim, K. S. Park, Estimation of thermal sensation based on wrist skin temperatures, *Sensors* 16 (2016) 420.
Video Magnification. https://people.csail.mit.edu/mrub/vidmag/
Wikipedia. https://en.wikipedia.org/wiki/Non-invasive_procedure
W. Jung, F. Jazizadeh,Vision-based thermal comfort quantification for HVAC control, *Build. Environ.* 220 (2018) 829–841.
W. Jung, F. Jazizadeh, Non-intrusive detection of respiration for smart control of HVAC System, In Proceedings of ASCE International Workshop on Computing in Civil Engineering, Seattle, Washington, USA, 25–27 June 2017, 310–317.
W. Li, J. Zhang. T. Zhao, R. Liang, Experimental research of online monitoring and evaluation method of human thermal sensation in different active states based on wristband device, *Energ. Build.* 173 (2018) 613–622.
W. Li, J. Zhang. T. Zhao, Optimization control method of indoor temperature based on wearable sensing of human thermal sensation, *HV&AC (Chinese journal)* 49 (2019) 26–31.
X. Cheng, B. Yang , A. Hedman, T. Olofsson, H. Li, L. V. Gool, NIDL: A pilot study of contactless measurement of skin temperature for intelligent building, *Energ. Build.* 198 (2019) 340–352.

X. Cheng, B. Yang, K. Tan, E. Isaksson, L. Li, A. Hedman, T. Olofsson, H. Li, A contactless measuring method of skin temperature based on the skin sensitivity index and deep learning, *Appl. Sci.* 9 (2019) 1375.
X. Cheng, B. Yang, T. Olofsson, G. Liu, H. Li, A pilot study of online non-invasive measuring technology based on video magnification to determine skin temperature, *Build. Environ.* 121 (2017) 1–10.
Y. Chen, B. Lu, Y. Chen, X. Feng, Breathable and stretchable temperature sensors inspired by skin, *Sci. Rep.* 5 (2015) 11505.
Z. Cao, T. Simon, S. E. Wei, Y. Sheikh, Realtime multi-person 2d pose estimation using part affinity fields, In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017, 7291–7299.
Z. Zhang, H. Zhang, T. Liu, Study on body temperature detection of pig based on infrared technology: A review, *Artif. Intell. Agr.* 1 (2019) 14–26.
Z. Zhu, P. Tsiamyrtzis, I. Pavlidis, Forehead thermal signature extraction in lie detection, In Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, France, 22–26 August 2007, 243–246.