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Real-time and contactless measurements of thermal discomfort based on human poses for energy efficient control of buildings

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Abstract: Individual thermal discomfort perception gives important feedback signals for energy efficient control of building heating, ventilation and air conditioning systems. However, there is few effective method to measure thermal discomfort status of occupants in a real-time and contactless way. A novel method based on contactless measurements of human thermal discomfort status was presented. Images of occupant poses, which are related to thermoregulation mechanisms, were captured by a digital camera and the corresponding 2D coordinates were obtained. These poses were converted into skeletal configurations. An algorithm was developed to recognize different poses related to thermal discomfort, such as hugging oneself or wiping sweat off the brow. The algorithm could recognize twelve thermal discomfort related human poses. These poses were derived from a questionnaire survey of 369 human subjects. Some other human subjects participated in the validation experiments of the proposed method. All twelve thermal discomfort related poses can be recognized effectively.

Keywords: Contactless measurement, Thermal discomfort, Human pose, Machine learning

1. Introduction

About 21% of global energy consumption occurs in building section, and roughly half of which is consumed by heating, ventilation and air conditioning (HVAC) systems in order to provide thermal comfort to their occupants [1, 2]. However, certain amount of HVAC related energy was wasted by overheating [3] and overcooling [4] beyond thermal comfort requirements. Intelligent management of energy and thermal comfort is necessary [5, 6]. Real-time and accurate measurements of occupant thermal comfort status can give feedback signals for demand control so as to reducing the energy consumption of HVAC systems. Many methods for evaluating human thermal comfort status have been proposed, including questionnaire survey, environmental parameters measurements, contactable physiological measurements and semi-contactable physiological measurements. Ghahramani used an infrared sensor, mounted on the frame of glasses, to measure skin temperature [7, 8]. However, not everybody wears glasses, which confines broad applications of the method. Smart watches are often adopted to check physiological processes despite the disadvantage of requiring contact [9]. Recently, contactless measurements of human thermal comfort status have been proposed, such as vision-based skin blood perfusion extractions and respiration quantifications [10, 11]. Vasoconstriction and poses reducing of body heat dissipation area happened when human feel cold. Vasodilation and poses fanning and wiping sweat happened when human feel hot [12]. Meier used Kinect to observe poses associated with thermal discomfort [13]. However, the Kinect is unique device used for computer gaming with exclusive patent rights, which is not user friendly and does not share platform or source code.

Thermal comfort is an individual, subjective feeling that constantly changes as the person interacts with the surrounding thermal environments [14, 15]. Human thermal comfort status can be obtained by objectively measuring thermal environment parameters or using occupant voting systems (OVS e.g., web-based or smartphone-app-based surveys provides accessibility, compared to conventional hard-copy questionnaires) [16, 17]. To avoid human participation, one contactless method for measuring human thermal discomfort is proposed. The method relies on poses obtained from the OpenPose model. A pose can be captured by a digital camera (easily available on smartphones and laptops) and is digitized. Twelve poses were defined that reflect human thermal comfort status. The OpenPose data were combined with thermal discomfort perceptions obtained through questionnaires, and a novel human pose recognition algorithm was constructed, including twelve sub-algorithms. The twelve poses can be estimated. Human subjects were invited for algorithm validation, and a big dataset was collected.

The main contributions of this paper are as follows:

(1) Twelve human poses of thermal discomfort were defined, based on 369 survey questionnaires;

(2) A method for estimating human thermal comfort status, based on data collected from normal computers or phone cameras, was demonstrated;

(3) A novel algorithm, based on the OpenPose, was developed for real-time and contactless measurements of human thermal comfort status.

The rest of this paper is organized as follows. In Section 2, related works about thermal comfort measurements are introduced. In Section 3, the research method, including pose definition and OpenPose platform, are introduced. Based on it , the human pose recognition algorithm is proposed. Data validation results and discussion are shown in Section 4. Finally, conclusions are given in Section 5.

2. Related work

Human thermal sensation is subjective feeling which involves human psychology and human environment interaction [14]. Fanger has explored thermal comfort since 1970s and founded his theory [14]. Based on it, many researchers study this topic in the past several decades.

Questionnaire survey is a useful and human-centered method to obtain subjective evaluations for thermal environments from occupants [18]. However, it is not always convenient for occupants to give their real-time feedback by conventional hard-copy questionnaires [19]. Web-based or smartphone-app-based surveys provides feasibility but need personal participation. For achieving the practical goal of maintaining acceptable thermal environments, the building section relies on measurements of environmental parameters, including indoor dry-bulb temperature, relative humidity, air speed and radiant temperature. From the perspective of constant indoor parameters, thermal comfort environment was defined, which is "at least 80% of building occupants are psychologically satisfied with the temperature range of thermal environment" [20, 21]. Liu [22] studied the individual thermal comfort and constructed a neural network-based model to overcome this problem, based on back propagation neural networks. Afroz [23] proposed a nonlinear autoregressive network to predict indoor temperature, where the network size was tuned for improving the efficiency of the prediction model. However, large inter- and intra-individual differences existed in human thermal comfort [15]. Different people have different feelings in the same indoor environments. Therefore, physiological measurement methods were explored by many researchers, including invasive measuring method, semi-invasive measuring method and contactless measuring method.

Skin temperature is an intermediate variable usually used for human thermal comfort estimation. Wang [24] studied the relationship between human thermal sensation and upper-extremity skin temperature. Nakayama [25] estimated human thermal sensation based peripheral skin temperature, and a subjective experiment was performed to analyze the relationship between peripheral skin temperature and subjective sensation votes. Liu [26], Takada [27], Sim [28], Wu [29] and Chaudhuri [30] proposed several methods to predict thermal comfort based on skin temperature. Heart rate variation (HRV) and electroencephalograph (EEG) were also explored. Yao [31] explored HRV and

EEG to estimate thermal comfort. The results show that HRV and EEG can be factors that reflect human thermal comfort. Further, machine learning method was introduced into invasive methods for physiological measurements. Chaudhuri [32] proposed a data-driven method and three thermal comfort levels were defined: cool discomfort, comfort and warm discomfort. Classifiers were constructed using these levels, based on support vector machine (SVM), artificial neural network (ANN), and logistic regression (LR). Dai [33] combined machine learning with skin temperature, and an intelligent control method based on SVM was proposed. The validation results show that three skin sampling points can produce enough information for estimating thermal comfort. The SVM classifier with linear kernel is better than that with Gaussian kernel. Kim [34] proposed a personal comfort models for predicting occupant thermal sensation. The data were collected from a personal comfort system (PCS), and machine learning was used for data analysis.

Semi-invasive measuring methods have also been investigated [7, 8]. Ghahramani [7] collected skin temperature from three sampling points around human eyes. The infrared sensors were constructed on eye glasses, and some subjects were invited for subjective experiments. Ghahramani [8] used unsupervised learning method to further analyze the collected data, and proposed a hidden Markov model to estimate skin temperature and thermal comfort.

The disadvantages of invasive measuring method and semi-invasive measuring method are obvious. The close-fitting sensor is required to collect human physiological parameters, which impedes broad application. As a solution, Cheng [35] used normal computers and cell phone cameras to predict human thermal comfort. Two saturation-temperature (ST) models were proposed, including contactless thermal comfort measurements based on ST model and contactless thermal comfort measurement based on partly ST model. In the study, subtleness magnification technology was adopted and the Euler Video Magnification was combined with big data to magnify skin features. The pilot study is a trial of contactless evaluation of thermal comfort, which is applicable under strong thermal stimuli for hand back skin.

In recent years, deep learning techniques have been applied to this problem [36]. Besides the study, many other researchers [32-34] attempted to combine machine learning and thermal comfort prediction. SVM was mainly used [37-39], and a public dataset were used for method validation. Peng [40] used unsupervised and supervised learning to predict occupant behavior. A demand-driven method was presented, which was validated in eleven rooms of a commercial building.

Recently, contactless evaluations of thermal discomfort have been proposed. Meier et al. employed a Kinect to observe gestures associated with thermal discomfort [13]. They defined 4 poses associated with thermal discomfort, established rule-based relationships, and detected them with the Kinect. They also proposed a “library of thermal discomfort gestures” to store the pose information. These methods have significant practical limitations. The Kinect is a unique device typically used for computer gaming and its use is protected by many exclusive patent rights. For the infrared sensor mounted on glasses, not everybody can be expected to wears glasses. The broad adoption of these technologies is therefore limited.

From the perspective of practical application, however, contactless measuring methods of assessing thermal discomfort remains an attractive research direction because human poses (or gestures) can reflect thermal discomfort status. The approach is more suitable to be applied to extreme situations such as industrial factories, which thermally discomfort behaviors happened frequently. With the development of deep learning technology, OpenPose was proposed and it is a deep learning-based open source platform [41-43]. OpenPose can produce key point coordinate of human skeleton and will be useful to estimate human thermal discomfort. Based on OpenPose, we proposed a contactless thermal discomfort perception method based on physiological factors.

3. Research method

3.1. Pose definition and questionnaire survey

Humans adopt various poses when they feel hot or cold. These are based on physiological responses but can be influenced by cultural factors and climate adaptations. Twelve thermal discomfort related poses were proposed and defined. As shown in Table 1, the poses are “wiping sweat”, “fanning with hands”, “shaking T-shirt”, “scratch head”, “roll up sleeves”, “walking”, “shoulder shaking”, “folded arm”, “leg cross”, “hands around neck”, “warm hands with breath”, and “stamping feet”. Further, the thermal discomfort level of wiping sweat and fanning with hands are ‘hot’, and the corresponding score is ‘3’. The other 10 poses have different thermal discomfort levels and scores. Fig. 1 and Fig. 2 show the continuous changes of twelve poses in the time dimension. Sitting and standing work positions are both considered in this paper. A total of 2 figures were shown in Fig. 1-2.

To assess whether the poses defined in this paper are related to human thermal sensations, a subjective questionnaire was used. The subjects were required to assess the twelve poses from the following options: (1) is it a cold action response? (2) is it a hot action response? or (3) neither. Meanwhile, whether subjects agreed to the pre-setting values in Table 2 were also asked. In addition, anthropometric data of subjects, including height, weight, gender and age, were collected. Based on the results of the questionnaire, the poses were used for algorithm design and validation. Totally 369 human subjects, including 199 males and 170 females, got involved the survey. Some elder subjects were invited to our research group to finish paper based questionnaire. Most of the young subjects finish their surveys by E-questionnaires through cell phone. Most of the subjects are University students, staffs and retired staffs.

3.2. Algorithm

The human body naturally adjusts its position to maximize thermal comfort. These movements of bones and joints will produce various changes in space. Let sp_i denotes the key points of human skeleton, since the images captured by normal camera is 2D, so that sp_i is

$$sp_i = [x_i, y_i], i = 0, \ldots, k \tag{1}$$

Where, x_i and y_i denote the horizontal and vertical coordinates in image space. The ‘i’ denotes different key points of human skeleton and its number. The ‘k’ is the maximum of key point number. If sp_i is obtained accurately, the corresponding algorithm can be constructed for computing the movements of the human body and recognizing human poses.

OpenPose is a kind of convolutional pose machine that can provide a sequential prediction framework for learning rich implicit spatial models [31-33]. Based on this, a human skeleton can be constructed in digital form. As shown in Fig. 3, there are 19 key points (k = 18). The key points of skeleton are nose, neck, right shoulder, right elbow, right wrist, left shoulder, left elbow, left wrist, right hip, right knee, right ankle, left hip, left knee, left ankle, right eye, left eye, right ear and left ear. The corresponding number is from 0 to 17. It should be noted that ‘i=18’ denotes the scene background.

The framework of the algorithm presented in this paper is shown in Fig. 4. If pooling and convolution were regarded as hidden layers, a total of 34 hidden layers were used. OpenPose was adopted to get key points of human skeleton directly. Based on the information of skeleton key points, we constructed an algorithm platform and 10 sub-algorithms to capture human poses. As shown in Fig.4, the images of an occupant, working in an office, is captured by a normal camera. After processing by the “preprocessing” and “OpenPose” modules, the key points coordinates with a confidence value (z) are outputted. If the confidence value is less than a threshold ($z < \varepsilon$), the images will be discarded in this paper. If $z \geq \varepsilon$, the images will be imputed into poses recognition module. Finally, the type of pose and its corresponding thermal discomfort level can be obtained.

In this paper, the threshold ε is 0.5. When our algorithm platform is working, video is imported from normal camera into the OpenPose. In one second, 24 or 30 pictures are collected. Each of these pictures will have a confidence value (z). Our algorithm platform will discard all the pictures with the confidence value less than 0.5 and store the pictures with the confidence value greater than or equal to 0.5 in a folder. The data of all the key points of human skeleton in the pictures will also be saved in one file.

A sub-algorithm for each pose estimation was developed. To simplify technical processing, “walk” and “stamping feet” belong to the same sub-algorithm. Similarly, “hands around neck” and “warm hands with breath” belong to the same sub-algorithm. Therefore, a total of 10 sub-algorithms were constructed for different poses in this study.

The distance (L) between the skeleton key points is the Euclidean distance. For convenience of calculation, a standard distance is defined in this study, that is

$$L_s = |sp_7 - sp_6| \tag{2}$$

Where sp_7 denotes the left wrist and sp_6 denotes the left elbow. Based on formula (2), the relative distance between the key points can be calculated.

$$L_r = \frac{L_s}{L} \tag{3}$$

different relative distance (L_r) will be computed, and different threshold of L_r will be set for different pose recognition. Further, L_{r_max} and L_{r_min} will be set for recognition of certain poses, which denote the extremum of L_r. In addition, the mathematical slope is assumed in our algorithm. Further, coordinate changes of key points in continuous image frames are also used for pose estimation. The details of the algorithm are shown in Table 2.

Table 1. Pose definition based on Fanger’s seven point scale.

No.	Pose category	Score	Thermal comfort Level
1	Wiping sweat	3	Hot
2	Fanning with hands	3	Hot
3	Shaking T-shirt	2	Warm
4	Scratch head	2	Warm
5	Roll up sleeves	1	Slight warm
6	Walking	0	Neutral
7	Shoulder shaking	-1	Slight cool
8	Folded arm	-2	Cool
9	Leg cross	-2	Cool
10	Hands around neck	-2	Cool
11	Warm hands with breath	-3	Cold
12	Stamping feet	-3	Cold

Table 2. Key steps in algorithm to evaluate thermal discomfort based on a contactless, pose-based method.

Algorithm

Output: Pose category, thermal comfort level ([-3, 3]), thermal preference (-1, 0, 1)

Step:

1. Surveillance video preprocessing
   (1) Frame extraction.
   (2) De-noise.
   (3) Region of interest (ROI).
2. Searching coordinates of key points
   (1) Calling OpenPose platform.
   (2) Generating Jason.
   (3) Saving valuable frames based on Confidence value (ε=0.5).
3. Generating coordinate matrix based on Jason (18×3).
4. Computing standard distance (α), define the nearest distance threshold (τ=1.5).
5. Pose and thermal comfort estimation.
   (1) Computing relative Euclidean distance.
   (2) Computing slope.
   (3) Computing movement speed.
   (4) A total of 10 sub-algorithms were constructed and called for twelve poses. The ‘walking’ and ‘stamping feet’ belong to the same sub-algorithm. The ‘hands around neck’ and ‘warm hands with breath’ belong to the same sub-algorithm.
   (5) The sub-algorithms are 1) wiping sweat, 2) fanning with hands, 3) shaking T-shirt, 4)

scratch head, 5) roll up sleeves, 6) walking and stamping feet, 7) shoulder shaking, 8) folded arm, 9) leg cross, 10) hands around neck, warm hands with breath.

(6) Some parameters set: 1) wiping sweat: L_r=1.8, 2) fanning with hands: L_{r_max}= 120, L_{r_min}= 80,
3) Shaking T-shirt: 1.8, 120 and 80 are all used. 4) scratch head: L_r= 1.8, 5) Roll up sleeves, L_r= 0.9, 6) walk: L_r= 1.8, 7) stamping feet: slope difference threshold is 30. 8) shoulder shaking: L_r= 1.5, 9) folded arm, L_r= 2, 10) leg cross: L_r= 1, 11) hands around neck and warm hands with breath: L_r= 3.

(7) The key points used for calculating $L_r$are different for different poses.

6. Optimize algorithm parameters.

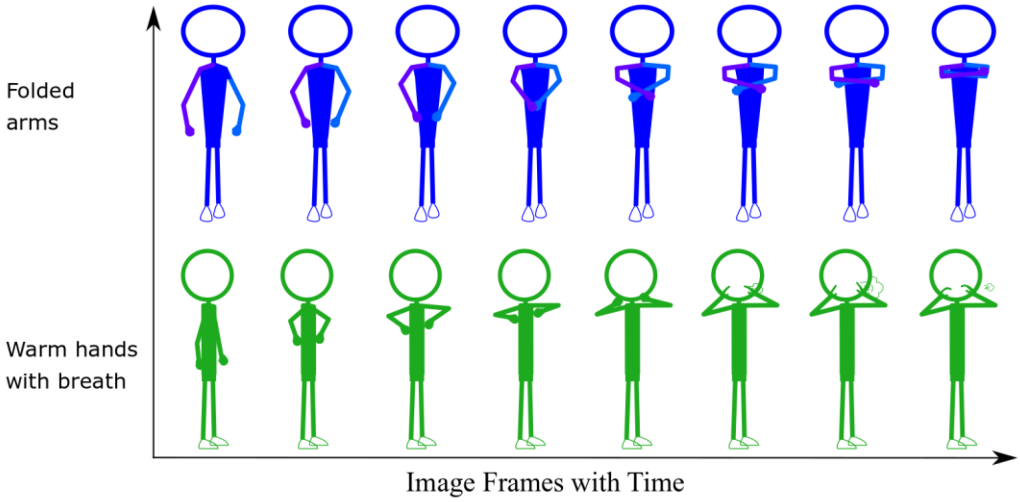


Fig. 1. Macro-pose example of cold sensation (1. 'Folded arms' and 'warm hands with breath' 2. The X axis denotes time. Like a movie, displaying each frames of a continuous motion 3. Only 2 poses of cold sensation were shown here as an exemplary example).

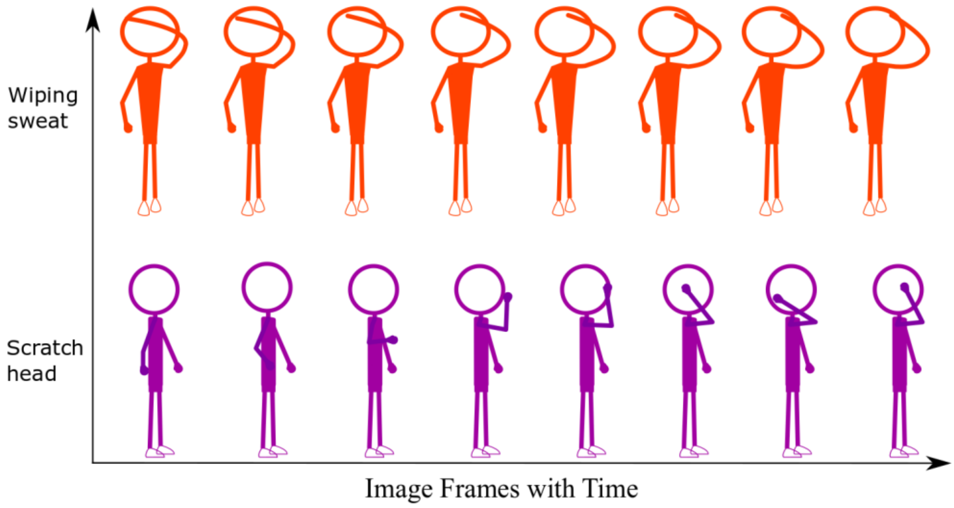


Fig. 2. Macro-pose example of hot sensation (1. 'Wiping sweat' and 'scratch head' 2. The X axis denotes time. Like a movie, displaying each frames of a continuous motion 3. Only 2 poses of hot sensation were shown here as an exemplary example).

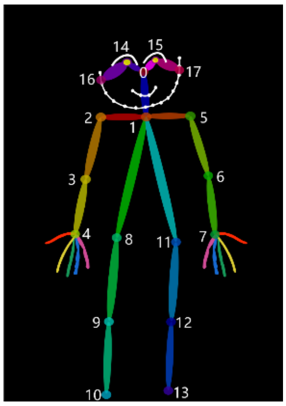


Fig. 3. Human skeleton and key points [31] (0. Nose 1. Neck 2. Right shoulder 3. Right elbow 4. Right wrist 5. Left shoulder 6. Left elbow 7. Left wrist 8. Right hip 9. Right knee 10. Right ankle 11. Left hip 12. Left knee 13. Left ankle 14. Right eye 15. Left eye16. Right ear 17. Left ear 18. Background).

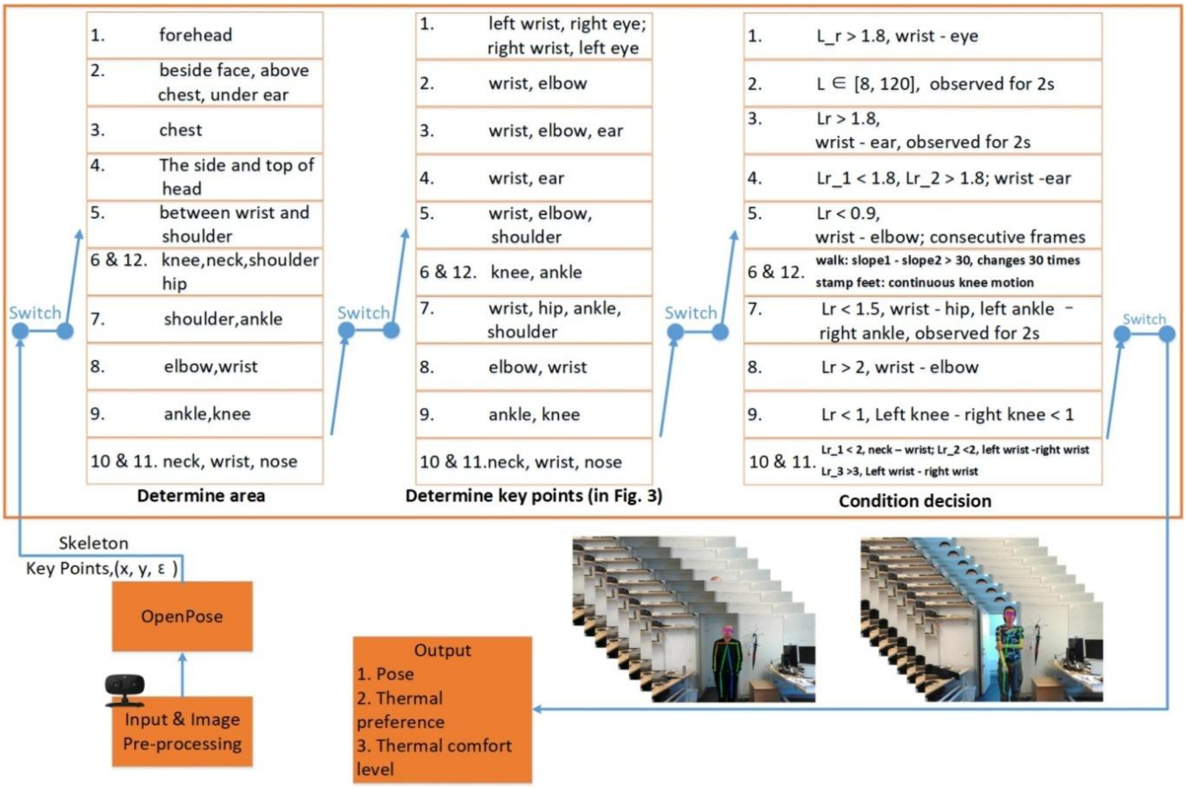


Fig. 4. Flow chart (For the twelve poses, 10 algorithms were designed. The 10 algorithms are summarized as three steps, including determine area, determine key points and conditional decision).

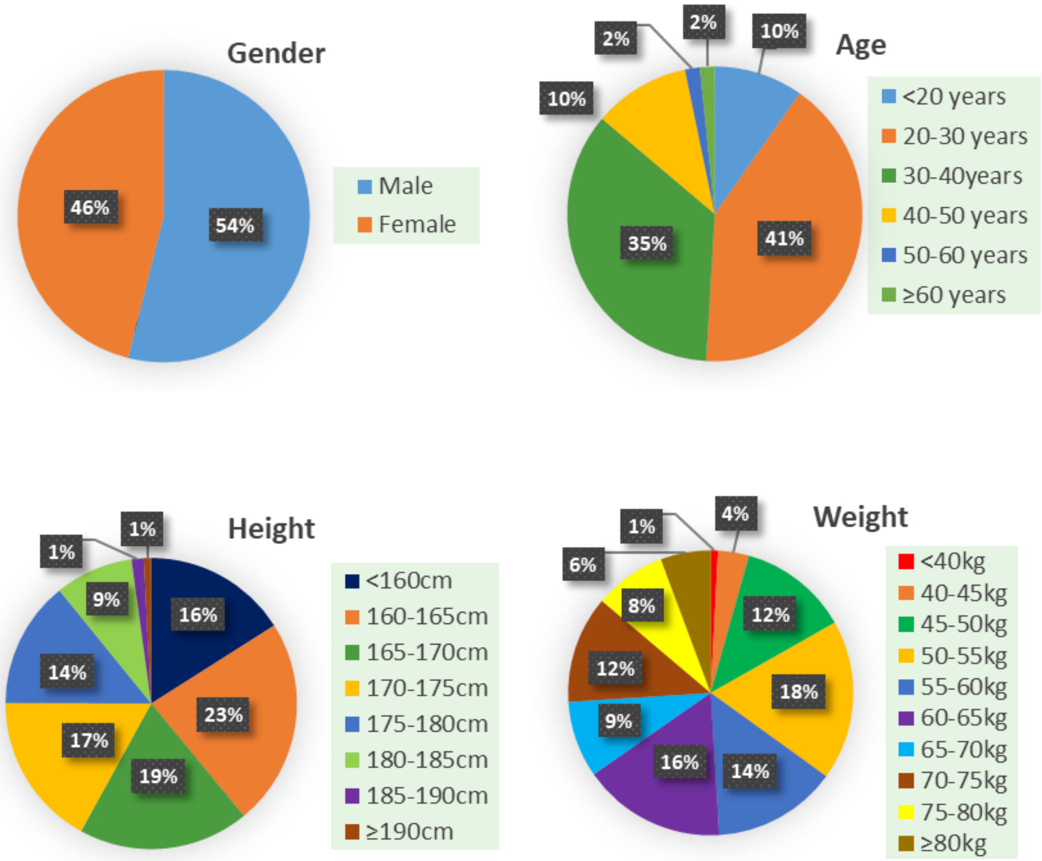


Fig. 5. Anthropometric data of subjects (Gender, age, height and weight).

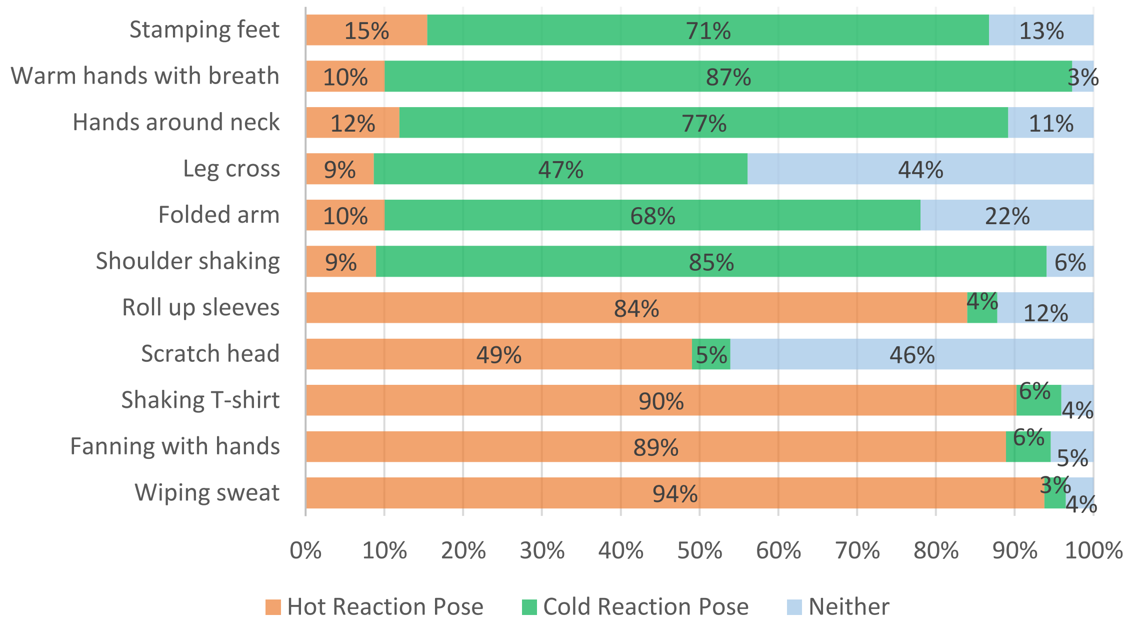
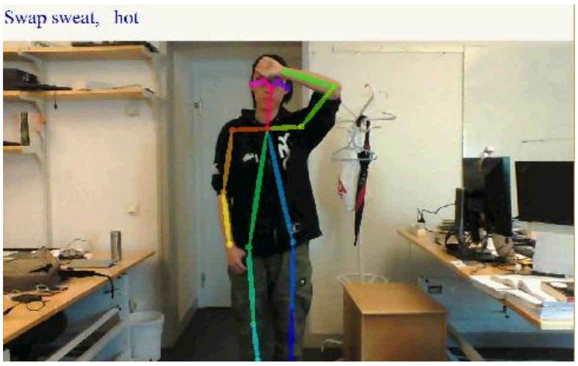
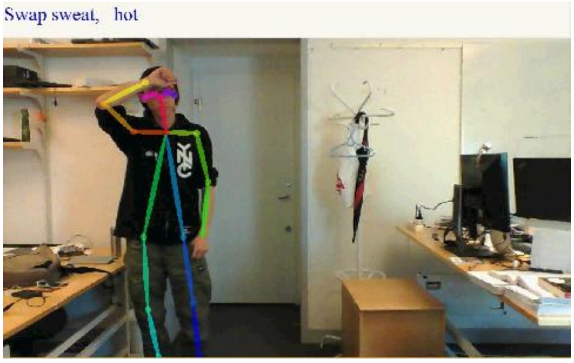


Fig. 6. Subjective interpretations of poses based on questionnaire (N=369).


Swap sweat, hot

(a)


Swap sweat, hot

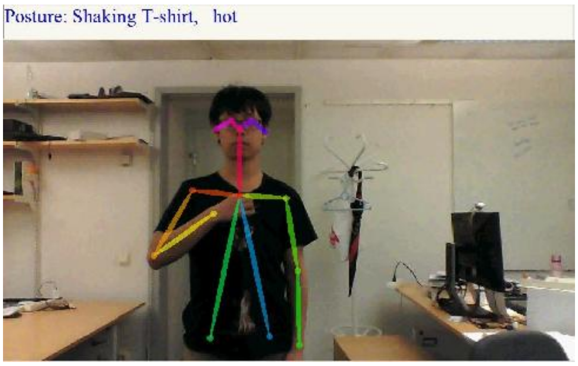
(b)


Fanning with hand, hot

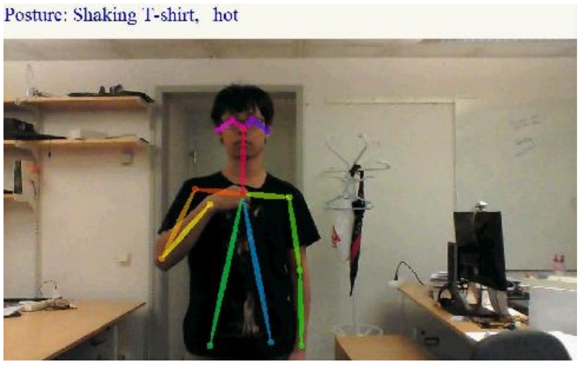
(c)


Fanning with hand, hot

(d)


Posture: Shaking T-shirt, hot

(e)


Posture: Shaking T-shirt, hot

(f)

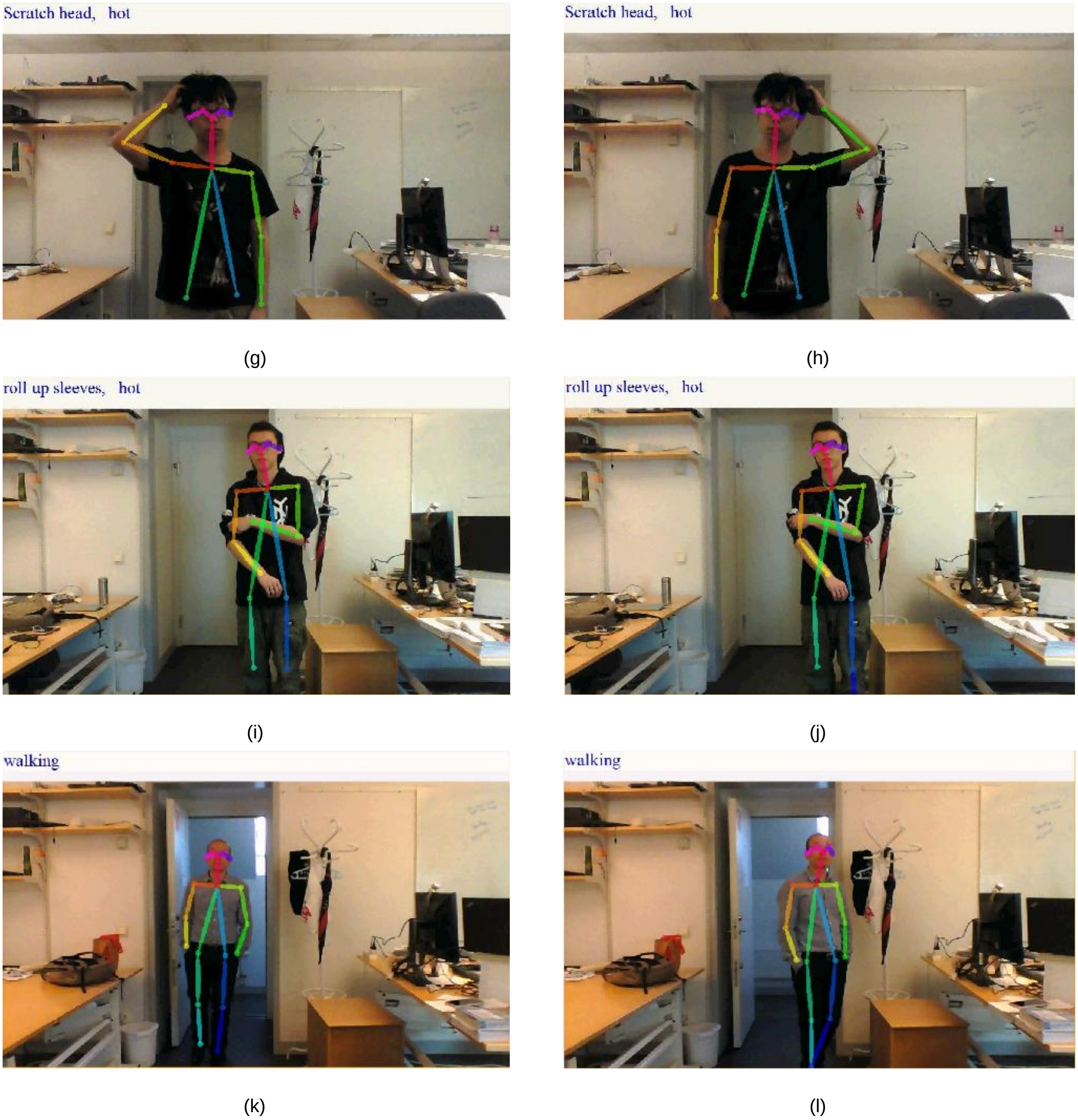
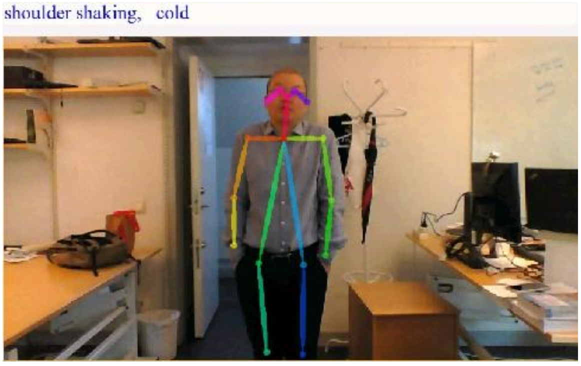
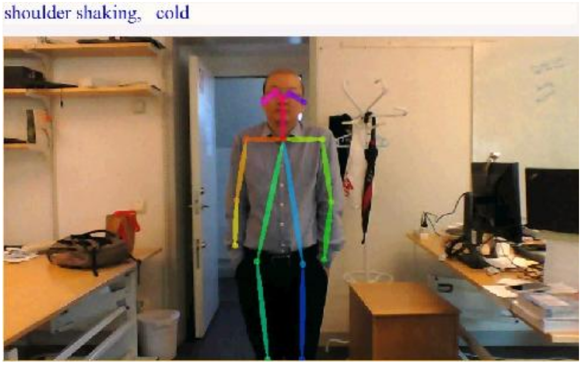


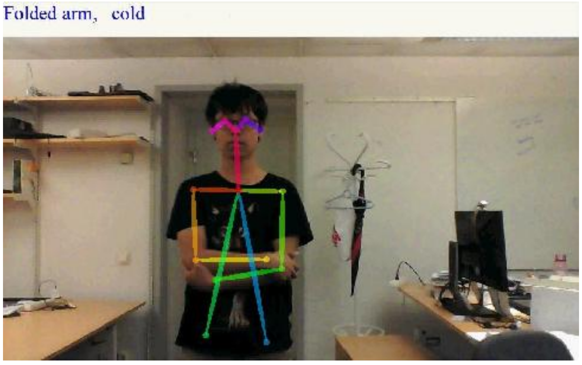
Fig. 7. Recognition results of hot and neutral poses by the algorithm proposed in this paper (Fig. 7.a-j denote the hot feeling poses: wiping sweat, fanning with hands, shaking T-shirt, scratch head and roll up sleeves respectively. Fig. 7.k-l denote the neutral feeling pose, e.g., walking.).


shoulder shaking, cold

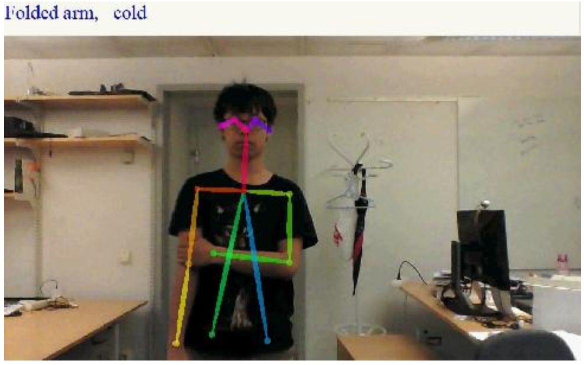
(a)


shoulder shaking, cold

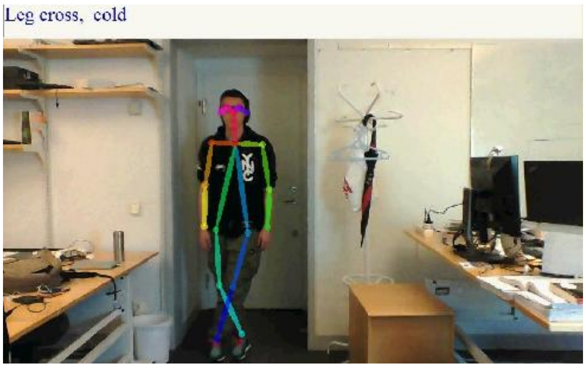
(b)


Folded arm, cold

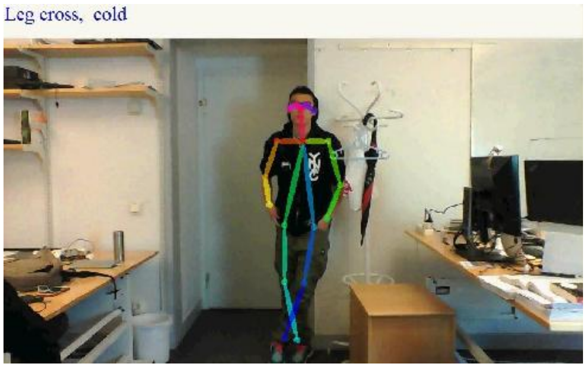
(c)


Folded arm, cold

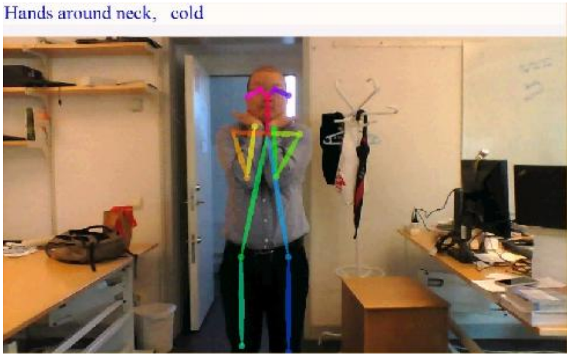
(d)

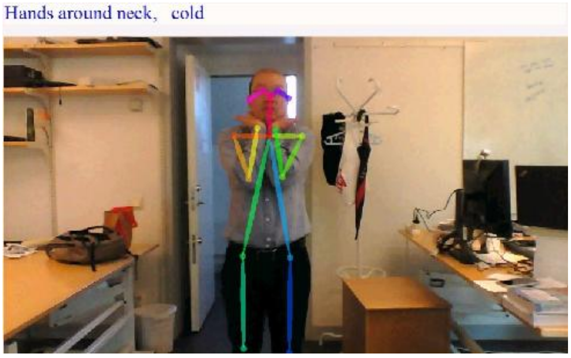

Leg cross, cold

(e)

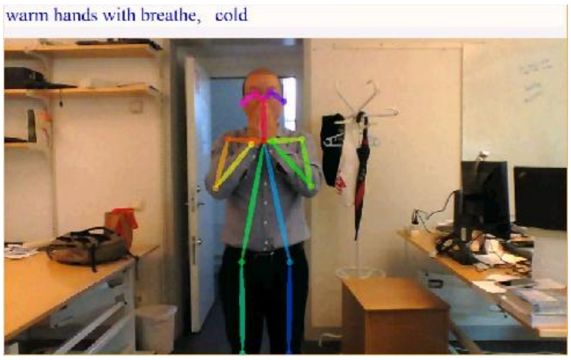

Leg cross, cold

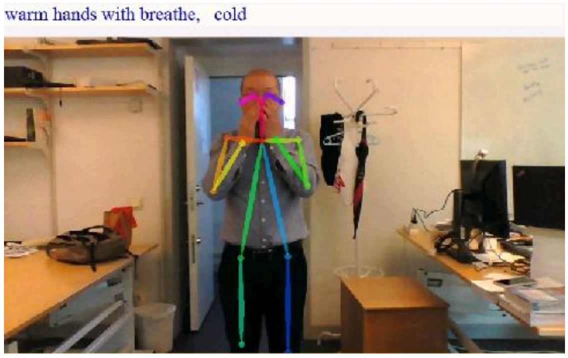
(f)



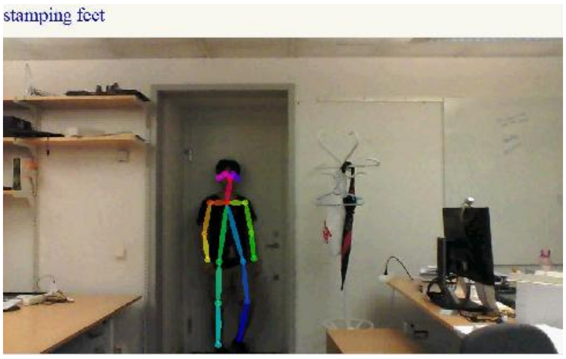


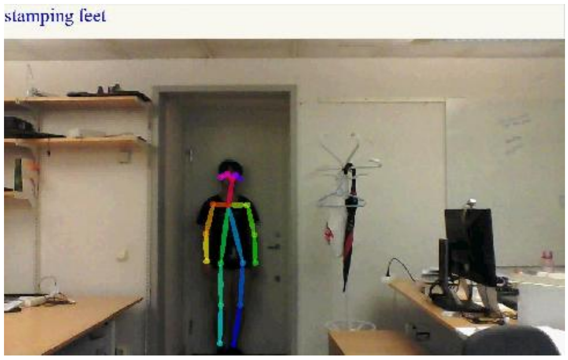
(g) (h)





(i) (j)





(k) (l)

Fig. 8. Recognition results of cold feeling poses by the algorithm proposed in this paper (The cold feeling poses are shoulder shaking, folded arm, leg cross, hands around neck, warm hands with breath and stamping feet, respectively).

4. Results and discussion

4.1. Results

To validate the contactless thermal discomfort perception method based on poses presented in this study, 369 subjects were invited to assess various human poses. In the algorithm validation, another group of human subjects participated in a real-time test.

In this paper, the algorithms were validated with a 64-bit computer workstation, with 32GB RAM. A graphics processing unit (GPU) was required for the algorithm training and testing. The GPU adopted in this study was NVIDIA GeForce GTX 980 (1920 × 1080, 32 bit, 60Hz), and the processor was Intel (R) Xeon (R) CPU E5-2687W V3 @ 3.10GHz.

Fig. 5 summarizes the results of all 369 valid questionnaires, consisting of 199 males and 170 females. Most subjects are between 20 years and 50 years. The subjects' heights were measured and binned into 5cm intervals. Among all the height intervals, the numbers of subjects whose height in

[160, 165), [165, 170), [170, 175), [175, 180), [180, 185), [185, 190) are 85, 70, 63, 52, 32 and 5, respectively. The intervals of weight is 5kg. Among all the weight intervals, the numbers of subjects whose weight in [40, 45), [45, 50), [50, 55), [55, 60), [60, 65), [65, 70), [70, 75), [75, 80) are 13, 46, 67, 52, 60, 32, 45 and 30, respectively.

Based on Fanger's steady state thermal comfort theory, we defined twelve poses which are hot sensation poses, neutral sensation poses and cold sensation poses. The poses are wiping sweat, fanning with hands, shaking T-shirt, scratch head, roll up sleeves, walking, shoulder shaking, folded arm, leg cross, hands around neck, warm hands with breath and stamping feet. In the questionnaire, all the subjects are required to assess the sensation of the poses defined in this study. It should be noted that the "walk" is a neutral pose and was not assessed in the questionnaire. The assessment results of 11 poses are shown in Fig. 6.The subjective assessment results of 9 of the eleven poses are fully consistent with expectations and the remaining 2 poses (leg cross and scratch head) are partially consistent with expectations. Fig. 6 shows that the definition of poses in this study is reasonably related to the thermal sensation of human daily life.

A practical application of the technique is shown in Fig. 4. All the images were captured by a digital camera and processed by the algorithm. To improve the accuracy of estimations, the twelve sub-algorithms are traversed according to a certain priority. The estimation results are shown in Fig. 7 and Fig.8. Human subjects were invited for algorithm validation. Fig. 7 is the validation results for the hot and neutral poses. The pose order of validation results are the same as that in Table 2. From Fig. 7-a to Fig. 7-l, the poses are wiping sweat, fanning with hands, shaking T-shirt, scratch head, roll up sleeves and walking, respectively. Fig. 8 is the validation results of cold poses. The corresponding poses are shoulder shaking, folded arm, leg cross, hands around neck, warm hands with breath and stamping feet, respectively. When the images were captured by a digital camera, the 2D coordinates could be obtained by OpenPose. Furthermore, the twelve sub-algorithms recognized the poses, based on these coordinate points.

Based on machine learning approaches, a kind of performance indicator, accuracy, was adopted in this study for algorithm validation. The accuracies for 12 poses were calculated. The mean value of these twelve accuracy values was calculated.

$$accuracy = \frac{F_{correct}}{F_{total}} \times 100\% \tag{4}$$

where, F_{total} is sample space of each poses. The F_{total} is the number of all video frames captured by the camera, when one of twelve poses was validated. $F_{correct}$ is video frames number of correct assessment in each sample space (F_{total}). Based on algorithm validation, the accuracy mean value of the algorithm proposed in this study is 86.37%.

4.2. Discussion and limitations

The study contributes to the growing number of techniques for contactless assessments of human thermal discomfort. Important new features were added, namely, real-time assessments to link results to a building's HVAC control system. Compared to previous contactless techniques that infer thermal comfort from skin temperature and color [35], pose based technique is less invasive because it acquires only the pose instead of unique personal, physiological information. Indeed, a better description of the technique is "remote" assessments of thermal discomfort.

The study shows that poses related to thermal discomfort can be identified. The survey demonstrates that twelve poses can be recognized and generally agreed upon by a large population. Two poses, leg cross and scratch head, are partly consistent with our expectations. For example, leg cross is a potential physiological response to cold because it reduces body surface area and heat loss. However, only 47% of the 369 subjects interprete it as a cold pose and 40% of the 369 interprete it as a pose that may be caused by other reasons, such as anger, frustration, pleasure, or fear. Possible solutions are as follows. If the behavior signal is used to control zonal HVAC systems, behavior signals from other occupants within the same thermal zone may validate whether the signal was caused by thermal discomfort or other reasons. Behavior cross validation between different occupants within the same zone can be used. If the behavior signal is used to control personal HVAC systems, cross validation between different behaviors of the same occupant can be used. For an instance, 'Leg cross' may happened together with 'Folded arm'. The frequency or intensity of the pose may be a clue to its interpretation. The “library of thermal discomfort gestures” proposed by Meier et al. [13] creates a framework for hundreds of gestures, some of which are used almost exclusively for thermal discomfort and others only occasionally.

There are inter- and intra-individual differences in human thermal comfort. The algorithm proposed here is a kind of real-time thermal discomfort perception method. The image frames (usually 24 or 30 frames/second) can be processed by the algorithm. The real-time pose variation can be captured, and the intra-individual differences can be overcome. In the design and commissioning phase of the algorithm, the relevant parameters were fine-tuned for different subjects, and a comprehensive parameter is given in this study. Inter-individual differences can be overcome by applying a population classification of relevant parameters.

This paper further demonstrates that it is possible to define the thermal poses in terms of skeletal key points. The combination of OpenPose software and algorithms described in this study could successfully recognize thermal discomfort poses. Furthermore, the process could be accomplished without depending on expensive hardware or proprietary software. The algorithm and a simple digital camera could be embedded into the computer server of a building’s HVAC system for wide use. However, collection of users’ images (videos) can be interpreted as invasive given privacy. Facial blurring process to avoid collection and storage of personally identifiable information should be used.

As mentioned in section 2 (related work), Meier [13] also studied human pose estimation for analyzing thermal discomfort. The main differences between the method of this study and that one [10] are shown as follows: 1) New algorithm platform. In this study, an algorithmic platform with extended function was constructed for other researchers to develop new sub-algorithms. 2) Sensor for data collection. In reference [13], Kinect obtains depth information through near-infrared camera, which in turn constructs skeleton point information. It should be noted that Kinect is protected by copyrights. In this study, OpenPose obtains skeleton point information through normal cameras with low price and strong expandability. Apart from OpenPose, our new algorithm platform can be used for other open source software. Based on it, more sub-algorithms of thermal uncomfortable poses estimation, not only for human beings but also for animals, can be developed by open source software.

In the progress of algorithm validation, some negative results were also generated occasionally. Generally it happened in the early stage of motion recognition. Based on key points of human skeleton, our algorithm was constructed to recognize thermal discomfort related poses. Specifically, it involves information such as key point displacement, slope, and comparison of connected frames. If one key point is identified incorrectly, following conditional judgment will be based on wrong key point information so as to causing wrong pose estimation. If the key point identification error occurs, the number of frames whose confidence values are less than 0.5, will decrease. 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.

Some research limitations should be mentioned here for future study. 1) A fundamental question. This study did not address a fundamental question. Does the absence of signals regarding thermal discomfort imply that the subjects are comfortable? The poses identified are physiological responses to thermal discomfort. Put another way, how uncomfortable must people become before they start exhibiting thermal uncomfortable poses? 2) Macro-and Micro-poses. In this paper, the human poses studied are hot/cold/neutral reaction poses, namely macro-poses. However, in practical applications, the motion magnitude of more poses related thermal comfort is very small and easy to be neglected, namely micro-poses. We will focus on micro-poses perception in the next step. 3) Real-time and delay. Real-time is a relative concept, although the algorithm proposed in this study achieved a real-time goals to certain extent, it is not enough. The recognition of all poses has a delay of about 1 second. The reason is that the algorithm needs time to process the recognition (usually 24 or 30 frames/second). In practical application, real-time is a very important requirement. Therefore, in the next step, we will do more validation and optimization for real-time cases, including the definition of accuracy, and the robustness of our algorithm. 4) Constructing own algorithm for capturing skeleton key points. By using third party software such as OpenPose platform, extended applications are confined. To overcome the limitations above, independent platforms will be developed for capturing key points of human skeletons in the next step. The 2nd to 4th points are mainly future research plans.

5. Conclusions

This paper examined a contactless method for evaluating a person's thermal sensation revealed by their poses. In the first phase, a survey was used to determine if poses could be attributed to thermal sensation. In the second phase, the algorithm was presented and tested. The conclusions can be summarized as follows.

- The twelve poses of thermal discomfort defined in this paper can be used for describing human thermal sensation;
- The algorithm presented in this paper is useful to recognize the twelve poses and the human thermal sensation level can be obtained;
- More abundant coordinate information of human body helps to perceive thermal poses accurately.

Future work will improve the algorithms, identify more poses, and calibrate the observed poses with traditional evaluations of thermal discomfort. Methods to avoid collection and storage of personally identifiable information will also be explored. Finally, the system will be linked to a building HVAC system in order to save energy.

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