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Abstract:

Individual thermal comfort perception plays very important roles in smart building and its energy efficiency control. However, there is no effective method to measure real-time thermal comfort of individual occupant until now. For overcoming the challenge of this case, including time-varying, individual difference and difficult to practical apply widely, a novel macro posed-based non-invasive perception method for thermal comfort (NIMAP) was presented. The occupant pose images were captured by normal phone camera (computer or cell phone) and the corresponding 2D coordinates can be obtained. Based on this, a novel pose recognition algorithm for thermal comfort, including 12 sub-algorithms, was presented. Then the 12 different macro poses of thermal comfort can be recognized. Further, based on Fanger's theory, 369 subjects are invited for subjective questionnaire. Finally, 3 human occupants participated in the validation of the method proposed and massive data was collected. The results is encourage and the 12 poses of thermal comfort all can be recognized effectively.

Keywords: Non-invasive measurement, Thermal comfort, Macro pose, Energy efficiency, Artificial intelligence

1. Introduction

21% of energy consumption of the world is that of residential and commercial buildings, and half of 21% is generated by Heating, Ventilation and Air Condition (HVAC) system [1-2]. Real-time and accurate measurement of occupant thermal comfort can reduce the energy consumption of HVAC, and the energy consumption of the entire building and block can be optimized. Many measurement methods for thermal comfort were proposed in the past few decades, including questionnaire, environment measurement, invasive physiological measurement and semi-invasive physiological measurement. Recently, some scholars use Kinect to measure human thermal preference [3], some researchers mounted an infrared sensor on the frame of glasses to measure skin temperature [4, 5]. However, thermal comfort is personal subjective feeling while the body interacts with indoor environment [6]. Due to some challenges existed, such as (1) individual difference between different occupants (2) time-varying of one occupant [6, 7], there is no effective method until now to perceive human thermal comfort in the practical application. Besides, Kinect is a kind of special device with exclusive patent rights, also not everyone wears glasses, so that the wide application possibility of study [3 - 5] is limited.

For overcoming the drawbacks described above, in this paper a non-invasive measuring method for human thermal comfort based on macro-pose (NIMAP) is presented. According Fanger's theory, we handled a subjective questionnaire with 369 subjects, and defined 12 macro-pose for human thermal preference. The occupant poses can be captured by normal compute or cell phone camera. The OpenPose was combined with thermal comfort perception, and a novel macro-pose recognition algorithm is constructed, including 12 sub-algorithms, so that the 12 macro-poses can be estimated. Finally, 3 human models are invited for algorithm validation, and a big dataset was collected.

The main contribution of this paper is summarized as follows:

(1) 369-person subjective questionnaire of thermal comfort were handled and 12 macro-poses of thermal comfort were defined based on Fanger's theory.
(2) It is the very first time that normal computer or phone camera was used for estimating thermal preference based on human poses. Thus the algorithm (NIMAP) proposed in this paper has the initial possibility of practical application.
(3) A novel algorithm (NIMAP) based on OpenPose was proposed for measuring human thermal preference, including 12 sub-algorithms. It is the very first time that OpenPose was combined with thermal comfort measurement.

The rest of this paper is organized as follows. Section 2 introduce the related work about thermal comfort measurement. In Section 3, the research method, including macro-pose definition and OpenPose platform, are introduced. Based on this, the micro-pose recognition

algorithm is proposed. The big data validation results and discussion are shown in Section 4 and 5. Finally, conclusions are given in Section 6.

2. Related work

Human thermal comfort is subjective feeling which involves human psychology and human interaction with the environment [6]. Fanger has been explored thermal comfort since 1970s and founded Fanger's theory [6]. Based on it, many researchers study this topic in the past several decades.

Questionnaire is a useful and humanistic method for capturing subjective feeling of occupant [8]. However, the operability is weak, because it is unrealistic for occupant to constantly feedback their personal feelings [9]. For solving the practical problem of building industry, environmental measurement method was adopted by human. Thereby, constant parameters, including indoor temperature, humidity and airflow, are measured for controlling indoor environment. Further, from the perspective of constant indoor parameters, ASHRAE and ISO (No. 7730) defined thermal comfort environment which is 'at least 80% of building occupants are psychologically satisfied with the temperature range of thermal environment' [10, 11]. Individual subjective feeling is ignored in environmental measurement method. For overcoming this problem, based on Back Propagation (BP) neural network, Liu [12] study the individual thermal comfort and constructed a neural network-based model. Afroz [13] proposed a nonlinear autoregressive network to predict indoor temperature, and the network size was tuned for improving the efficiency of prediction model. However, the inter- and intra-individual differences are exist in human thermal comfort [7], so that different people has different feeling in the same indoor environment. Therefore, physiological measurement method was explored by many researchers, including invasive measuring method, semi-invasive measuring method and non-invasive measuring method.

Invasive measuring method was appeared in early. Firstly, skin temperature is an intermediate variable usually used for human thermal comfort estimation. Wang [14] studied the relationship between human thermal sensation and upper-extremity skin temperature. Nakayama [15] estimated human thermal sensation based peripheral skin temperature, and a subjective experiment was handled to analyze the relationship between peripheral skin temperature and subjective sensation votes. From then on, Liu [16], Takada [17], Sim [18], Wu [19] and Chaudhuri [20] proposed all kinds of methods to predict thermal comfort based on skin temperature. Secondly, the heart rate variation (HRV) and electroencephalograph (EEG) are studied. Yao [21] explored HRV and EEG to estimate thermal comfort. The results show that HRV and EEG can be factors to reflect human thermal comfort. Further, some scholars introduce machine learning into invasive physiological measurement method. Chaudhuri [22] proposed a data-driven method and 3 thermal comfort levels were defined which are cool-discomfort, comfort and warm discomfort. Based on this, support vector machine (SVM), artificial neural network (ANN), and logistic regression (LR), *etc* are used for constructing classifiers. Dai [23] combined machine learning with skin temperature, and an intelligent control method based on SVM was proposed. The validation results show that 3 skin sampling points can produce enough information for estimating thermal comfort, and the SVM classifier with linear kernel is better than that with Gaussian kernel. Kim [24] proposed a personal comfort models for predicting occupant thermal sensation. The data was collected from a personal comfort system (PCS) chair, and machine learning was used for data analysis.

Semi-invasive measuring method was presented in study [4, 5]. Ghahramani [4] collected skin temperature from 3 sampling points around human eyes. The infrared sensors are constructed on eye glasses, and some subjects are invited for subjective experiment. Further, Ghahramani [5] use unsupervised learning method to further analyze the data collected in study [4], 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. Because the close-fitting sensor is required to collect human physiological parameters, thereby the widely practical application is limited. For overcoming this drawbacks, Cheng and Yang [25] use normal computer and cell phone camera to predict human thermal comfort. Two saturation-temperature (ST) models were proposed, including non-invasive thermal comfort measurement based on ST model (NIST) and non-invasive thermal comfort measurement based on partly ST model (NISPT). In the study [25], the first time that subtleness magnification technology was adopted and the Euler Video Magnification (EVM) was combined with big data to magnify skin features. The study [25] is a meaningful attempt in non-invasive thermal comfort perception.

In recent years, the deep learning is booming [26], besides the study [22-24], many other researchers made some meaningful attempts in the combination of machine learning and thermal comfort prediction. The mainly machine learning method they used is SVM [27-29], and public dataset was used for method validation. Further, Peng [30] use unsupervised and supervised learning to predict occupant behavior, and a demand-driven method was presented which was validated in 11 rooms of a commercial building.

From the perspective of practical application, non-invasive measuring method of thermal comfort is the

research direction in building industry. Further, human posture can reflect the thermal comfort of human body. With the development of deep learning technology, OpenPose is proposed and it is a deep learning-based open source platform [31-33]. OpenPose can produce key point coordinate of human skeleton and will be useful to estimate human thermal comfort. In this paper, based on OpenPose, we propose a thermal comfort perception method (NIMAP) which is belong to non-invasive physiological measurement method.

3. Research method

3.1 Macro-pose definition and questionnaire

Human will naturally have various postures when they feel hot or cold. Thereby, based on Fanger's theory of thermal comfort, we defined 12 macro-poses. As shown in Table 1, the macro-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 comfort level of wiping sweat and fanning with hands are 'hot', and the corresponding score is '3'. The other 10 poses have different thermal comfort level and score too. Fig. 1 and Fig. 2 show the continuous changes of 12 macro-poses in the time dimension. Sitting work style and standing work style are both considered in this paper, so that a total of 4 sub-fig were shown in Fig. 1-2.

In order to assess whether the macro-poses defined in this paper are in line with the human thermal sensation, a subjective questionnaire will be handled in this paper. All the subjects of questionnaire are required to assess the 12 macro-poses, and the options are (1) is it a cold action response, (2) is it a heat action response, or (3) neither. In addition, personal information of subjects, including height, weight, gender and age, will be collected. Based on the results of questionnaire, the macro-poses which is in line with the human body's sensation feeling will be used for algorithm design and validation.

3.2 Algorithm

When human body naturally makes all kinds of poses about thermal comfort, the 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

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

where, x_i and y_i denote the horizontal and vertical coordinates in image space. The 'i' denotes different key point 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 human body and recognizing human poses.

OpenPose is a kind of convolutional pose machines which can provide a sequential prediction framework for learning rich implicit spatial models [31-33]. Based on this, a human skeleton can be obtained. As shown in Fig. 3, there are 19 key points ($k = 19$). 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 NIMAP algorithm presented in this paper is shown in Fig. 4. The images of occupant, work in office, is captured by normal computer camera. After processing by 'preprocessing' module and 'OpenPose' module, the key points coordinates with confidence value (z) will 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 macro-poses and its corresponding thermal comfort level can be obtained.

For poses recognition, we designed a sub-algorithm for each pose estimation. Due to the need of technical processing, 'walk' and 'stamping feet' belong to the same sub-algorithm. Further, '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 macro-poses in this paper.

The distance (L) between the skeleton key points is European distance. For convenience of calculation, a standard distance is defined in this paper, 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 computed as

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

different relative distance (L_r) will be computed, and different threshold of L_r will be set for different poses recognition. Further, L_{r_max} and L_{r_min} will be set for some poses recognition which denote the extremum of L_r. In addition, mathematical slope is adopted in our algorithm. Further, coordinate changes of key points in continuous image frames are also used for pose estimation. The details of NIMAP algorithm is shown in Table 1.

TABLE 1. Pose definition based on Fanger's seven point scale

No.	Pose category	Score	Thermal comfort Level	Can NIMAP recognize the pose or not
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	√

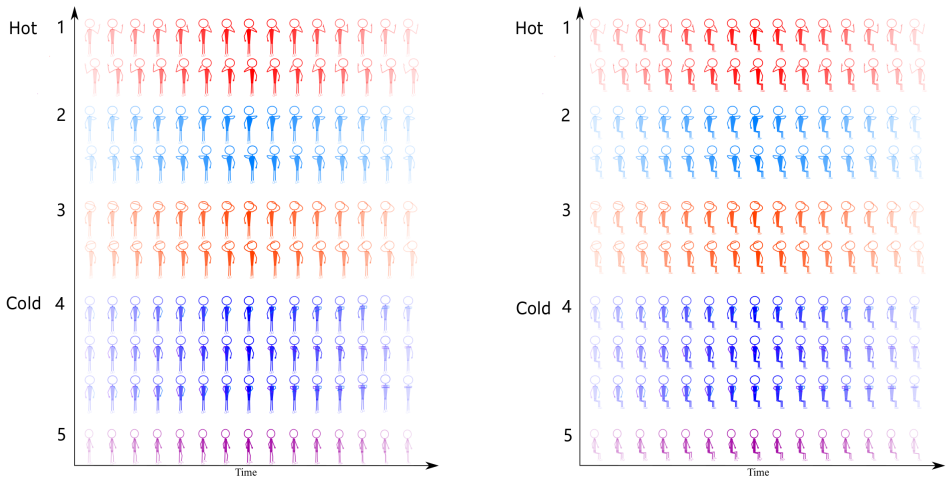
TABLE 2. Macro pose-based non-invasive thermal comfort perception for energy efficiency

Algorithm: NIMAP

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

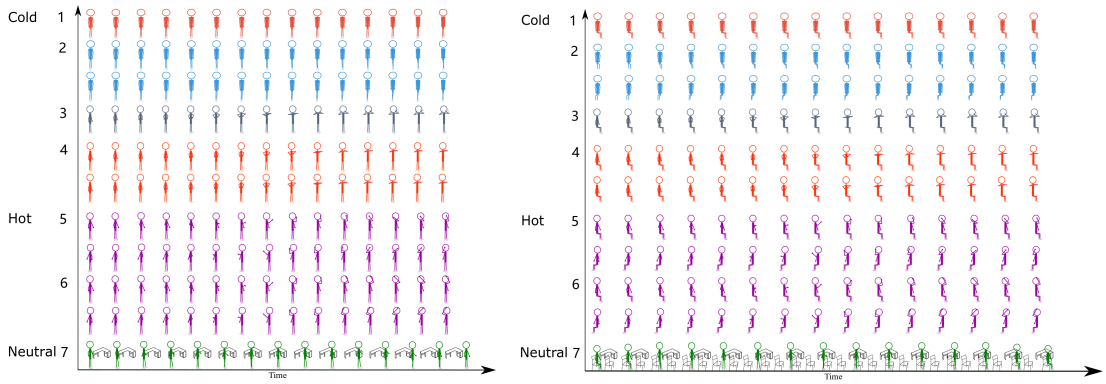
Step:

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 12 macro-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 macro-poses.
6. Optimize algorithm parameters.



(a) (b)

Fig. 1. Macro-pose of thermal comfort Part A ((1) a. stand work style b. seated work style. (2) in Fig. 1, '1' to '5' respectively denote fanning with hands, shaking T-shirt, wiping sweat, folded arms and stamping feet).



(a) (b)

Fig. 2. Macro-pose of thermal comfort Part B ((1) a. stand work style b. seated work style. (2) in Fig. 2, '1' to '6' respectively denote shoulder shaking, leg cross, warm hands with breath, hands around neck, scratch the side of head, scratch the top of head and walking).

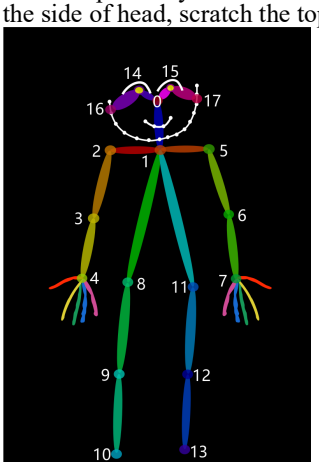


Fig. 3. Human skeleton and key points [31] (0. Nose 1. Neck 2. Right shoulder 3. Right elbow 4. Right wrist 5. Left shoulder 6. Left elbow 7. Left wrist 8. Right hip 9. Right knee 10. Right ankle 11. Left hip 12. Left knee 13. Left ankle 14. Right eye 15. Left eye 16. Right ear 17. Left ear 18. Background).

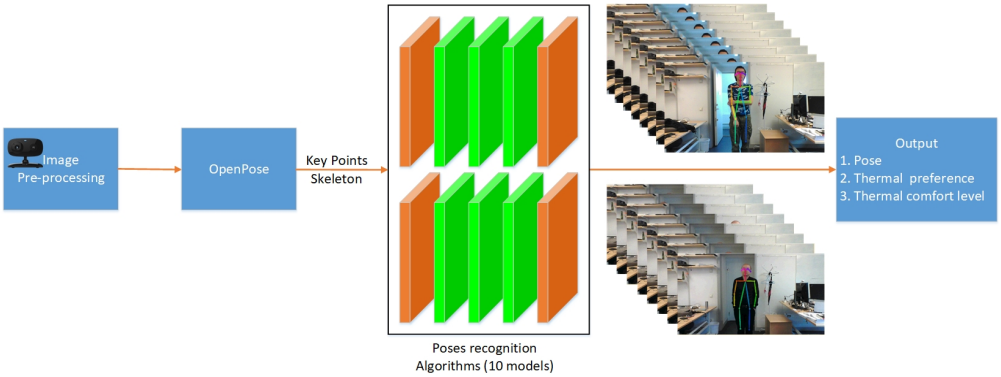


Fig. 4. The NIMAP network framework.

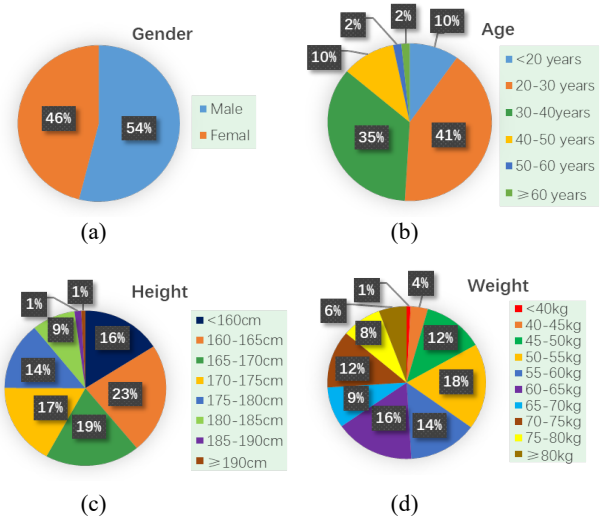


Fig. 5. Subjects information (Gender, age, height and weight).

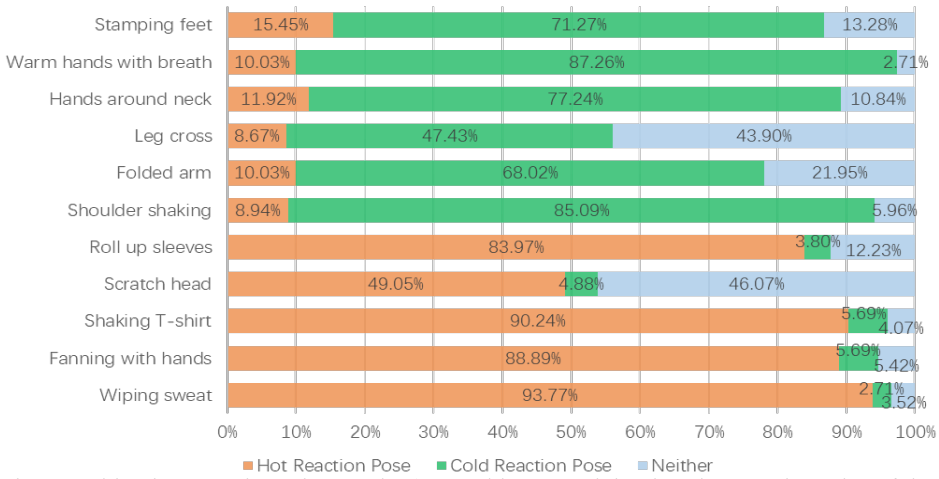
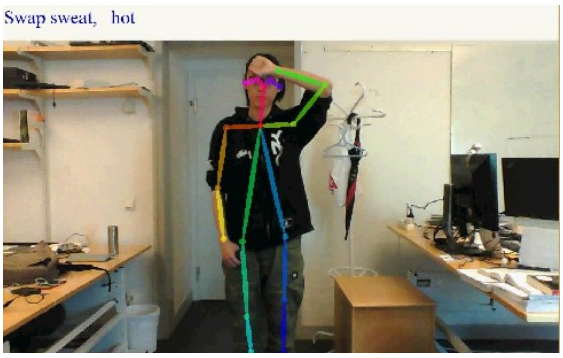
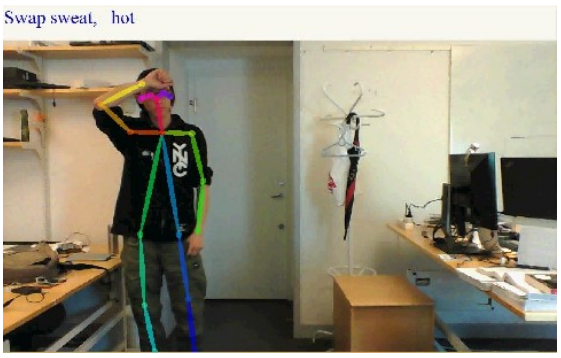


Fig. 6. Subjective questionnaire results (369 subjects participating the questionnaire of thermal comfort reaction).


Swap sweat, hot

(a)


Swap sweat, hot

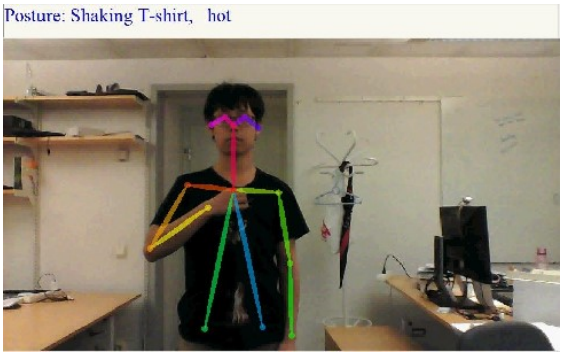
(b)

Fanning with hand, hot

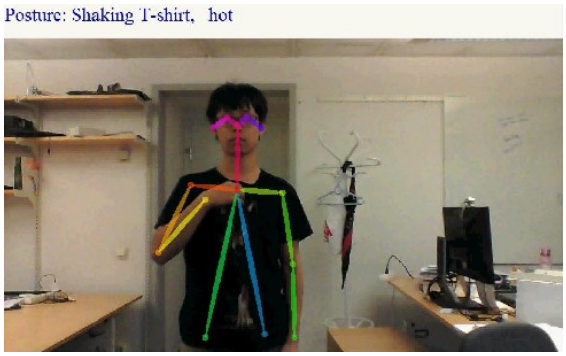
(c)

Fanning with hand, hot

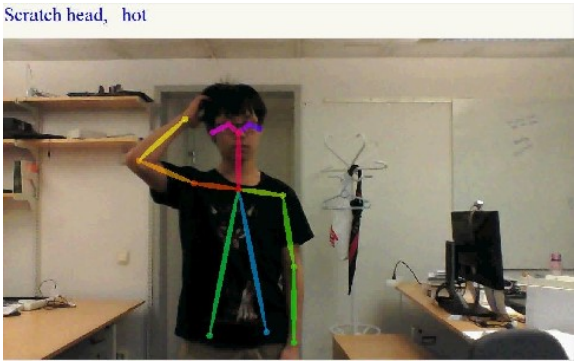
(d)


Posture: Shaking T-shirt, hot

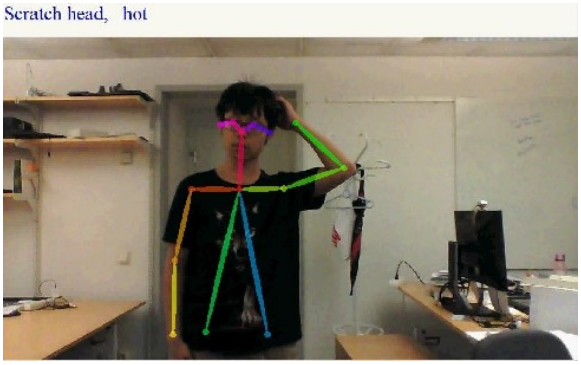
(e)


Posture: Shaking T-shirt, hot

(f)



(g)



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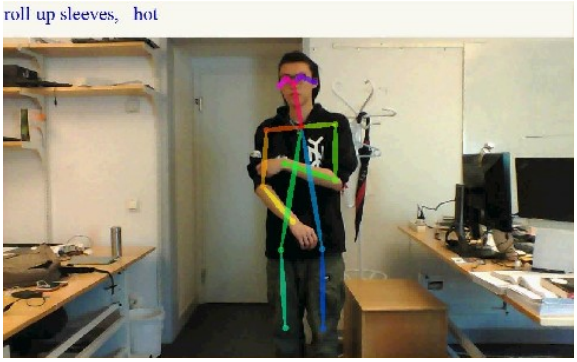
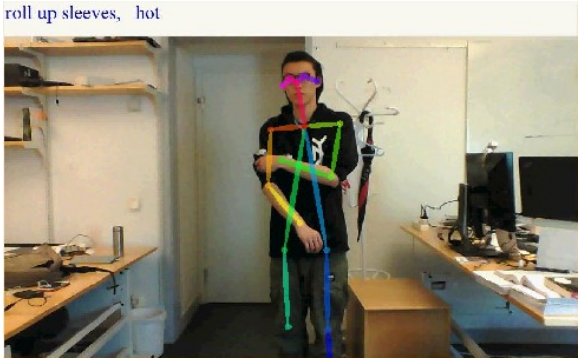
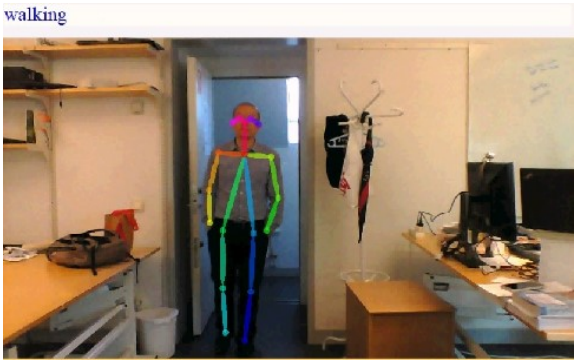


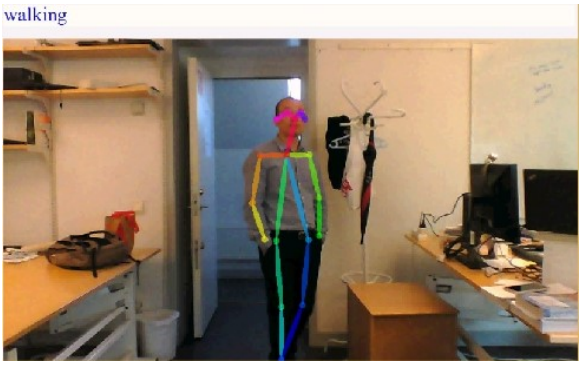
(i)



(j)



(k)

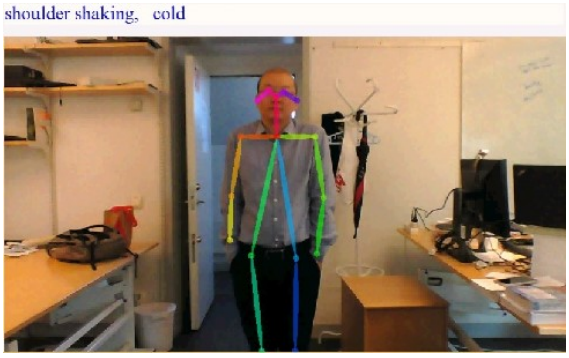


(l)

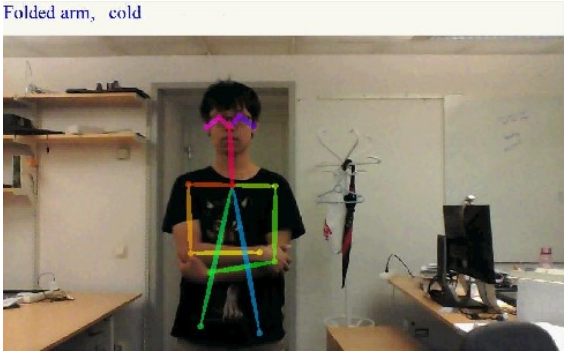
Fig. 7 Recognition results of hot and neutral poses by NIMAP algorithm proposed in this paper (Fig. 7.a-j denote the hot feeling poses which are wiping sweat, fanning with hands, shaking T-shirt, scratch head and roll up sleeves respectively. Fig. 7.k-I denote the neutral feeling poses which is walking.).

shoulder shaking, cold

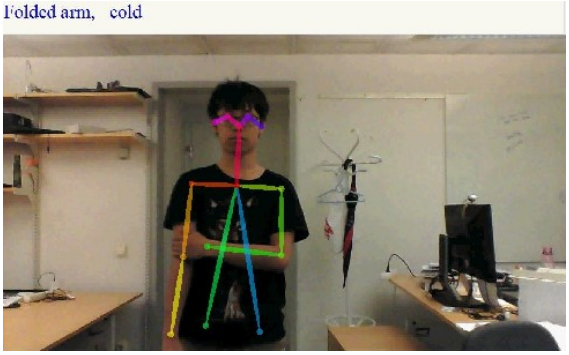
(a)


shoulder shaking, cold

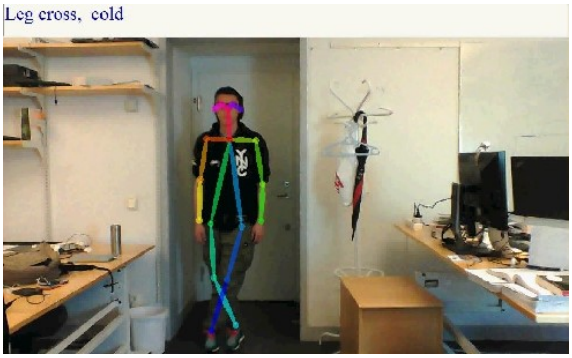
(b)


Folded arm, cold

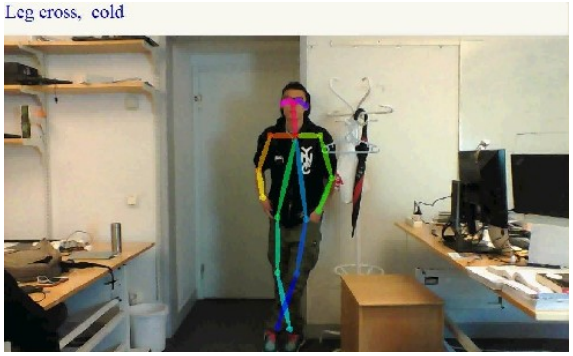
(c)


Folded arm, cold

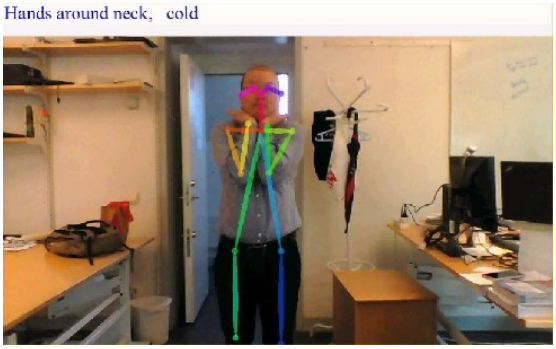
(d)


Leg cross, cold

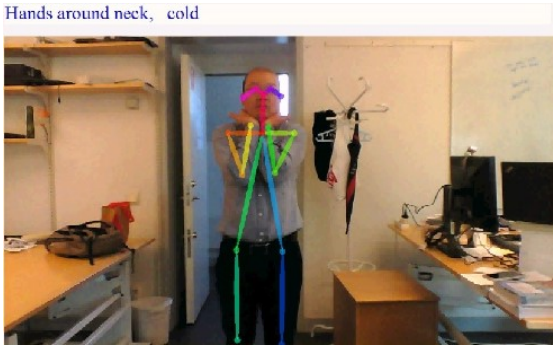
(e)


Leg cross, cold

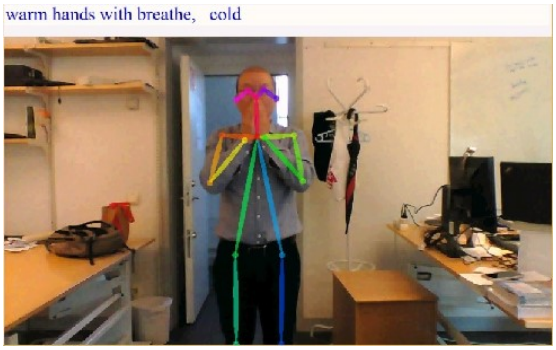
(f)



(g)

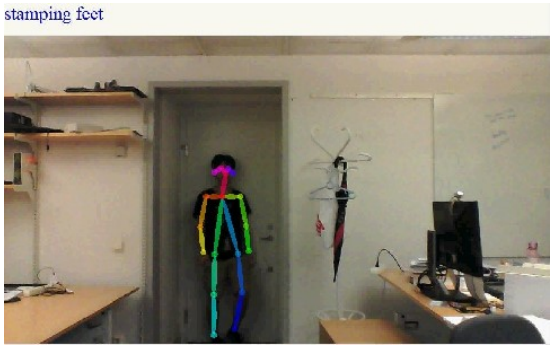


(h)

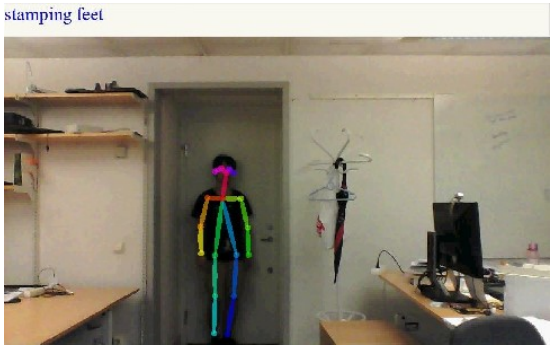


(i)

(j)



(k)



(l)

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

4. Results

To validate the non-invasive thermal comfort perception method based on macro poses (NIMAP) presented in this paper, a subjective questionnaire was explored and a total of 369 valid questionnaire were collected for defining thermal comfort poses. Further, an algorithm validation experiment were handled, and 3 subjects are invited for real-time test.

In this paper, a computer workstation, with 64-bit version and 32G RAM, was used for algorithm validation. Graphics processing unit (GPU) is required in the process of algorithm training and test. The GPU adopted in this paper is NVIDIA GeForce GTX 980 (1920 × 1080, 32 bit, 60Hz), and the processor is Intel (R) Xeon (R) CPU E5-2687W V3 @ 3.10GHz.

As shown in Fig. 5, in all the subjects who output valid questionnaires, male and female are 199 and 170, respectively, which is relative balance. The age of most of the subjects are between 20 years and 50 years. Among them, two age ranges which are [20, 30) and [30, 40) accounted for 35% and 41%, respectively. Subject height statistics were performed at intervals of 5 cm. 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.

Based on Fanger's theory of thermal comfort, we defined 12 macro-poses which are hot reaction pose, neutral pose and cold reaction pose. 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 questionnaire, all the subjects are required to assess the sensation of the 12 macro-poses defined in this paper, and the assessment results are shown in Fig. 6. The subjective assessment results of 10 of 12 macro-poses are fully consistent with our expectations and that of the remaining 2 poses are partially consistent with expectations. Fig. 6 shows that the definition of macro-poses in this paper is reasonable and meets the thermal sensation of human daily life.

As shown in Fig. 4, in practical application, all the images captured by normal computer camera will be processing by NIMAP algorithm. For improving estimating accuracy, when one image was inputted into NIMAP algorithm, the 12 sub-algorithms will be traversed according to a certain priority. The estimation results are shown in Fig. 7-8. A total of 3 subjects are 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-I, 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 breathe and stamping feet, respectively. When the images were captured by normal computer or cell phone camera, the 2D coordinates can be obtained by OpenPose firstly. Further, the 12 sub-algorithms can recognize the poses based these coordinate point. In addition, the Euclidean distance and mathematical slope are adopted in this paper for poses recognition. The conditional thresholds of poses recognition used in this paper shown in Table 2.

5. Discussion

The large number of samples questionnaire handled in this paper show that the 12 macro poses defined is reasonable. Further, the validation results shown in Fig. 7-8 show that the 2D coordinates of the skeleton key points, as well as the displacement and slope changes of the coordinates, are very useful to the recognition of the thermal comfort poses.

Kinect were used for measuring human metabolism and thermal comfort which are meaningful attempt. However, the patent and price of Kinect make a limited practical application. In this paper, a normal computer camera or cell phone camera is required for the NIMAP proposed. Further, the NIMAP algorithm can be embedded into computer server of HVAC in building. Thereby it is convenient for practical application.

There are inter- and intra-individual differences in human thermal comfort. The NIMAP proposed is a kind of real-time thermal comfort perception method. The image frames (usually 30 or 24 frames/second) can be processed by NIMAP algorithm. Thereby, the real-time pose variation can be captured, and the intra-individual differences can be overcome. In the design and commissioning phase of the NIMAP algorithm, the relevant parameters were fine-tuned for different subjects, and a comprehensive parameter is given in this paper. In further applications, different parameters will be adopted according to population classification. So that the inter-individual differences can be overcome.

The study [25] is another meaningful attempt in non-invasive perception of thermal comfort. The differences between this paper and study [25] are shown as follow (1) the study [25] is from the perspective of skin color variation. However, human poses of sensation are used for feature extraction in this paper. (2) the output of the study [25] is predication values of skin temperature, and that of this paper is thermal comfort level and the type of human poses.

It should be noted that deep information of human body

and office scene is not adopted in this paper. Signals interference with each other will happen, e.g. stamping feet and walk are sometimes misjudged during the debugging process. For overcoming this interference, more determine statements were used in the 12 sub-algorithms.

In questionnaire, the results of 2 of 12 poses defined in this paper, leg cross and scratch head, are just partly consistent with our expectation. For example, leg cross is a cold poses, but only 47.43% of the 369 subjects thought it is a cold poses, and 43.9% of the 369 subjects thought it is neither cold poses nor hot poses. There is similar results for scratch head. Thereby, some researcher maybe argue that why we still design the recognition algorithm for 'leg cross' and 'scratch head'? The reasons are as follows (1) it seems that there are description ambiguous for poses, leg cross and scratch head, in our questionnaire. So that the two poses were misunderstood by some subjects. Thereby, we still think that people will cross and stick their legs to warm when they feel cold. On the other hand, people will scratch side of head or top of head when they feel hot. (2) Even the two poses are not typical poses of thermal comfort, we would like to provide a kind of recognition method. So that it can be used in practical application if it is necessary.

6. Conclusion

The aim of this paper is to study a kind of non-invasive perception method of thermal comfort from macro-poses perspective. Based on Fanger's theory of thermal comfort, the subjective questionnaire was explored and the NIMAP algorithm was presented. The conclusion can be summarized as follows.

(1) The 12 macro-poses of thermal comfort defined in this paper can be used for descripting human thermal sensation.
(2) The NIMAP algorithm presented in this paper is useful to recognize the 12 macro-poses and the human sensation level can be obtained.
(3) More abundant coordinate information of human body helps to perceive thermal poses accurately.

It should be noted that deep information of human body will be useful to perceive the human comfort sensation. It will be our work in next step.

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