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Personal thermal comfort models based on physiological parameters measured by wearable sensors

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Abstract: Existing HVAC systems involve little feedback from indoor occupants, resulting in unnecessary cooling/heating waste and high percentage of discomfort. In addition, large thermal preference variance amongst people requires the development of personal thermal comfort models, rather than group-based methodologies such as predicted mean vote (PMV). This study focuses on assessing wearable solutions with the aim to predict personal thermal preference. We collected physiological signals (e.g., skin temperature, heart rate) of 14 subjects (6 female and 8 male adults) and environmental parameters (e.g., air temperature, wind speed, solar radiation, precipitation) for two weeks (at least 20 hr/d) to infer personal real-time thermal preference. The subjects reported their real-time thermal sensation and preference using cell-phones approximately every hour. We trained a Random Forest algorithm using data collected from individuals to develop a personal comfort model with the objective to predict thermal preference. The results show that subjects expressed needs for “warmer” or “cooler” conditions at about 30% (from 21% to 88%) of their daily time on average, implying the strong demand for a personalized indoor thermal comfort. In addition, the personal comfort model using Random Forest can infer individual thermal preference with a mean accuracy of 75% (53 - 93%) using physiological and environmental parameters, demonstrating the strengths of the proposed data-driven method.

Keywords: Thermal preference, physiological signals/responses, Random Forest, skin temperature, heart rate

1. Introduction

Creating a thermally comfortable indoor environment for occupants can lead to improved job satisfaction, productivity and well-being. Only 40% of the occupant in US commercial buildings are satisfied with the thermal environment (Karmann et al., 2018). Perceived productivity was found reduced when thermal preference moved away from “no change” (McCartney and Humphreys, 2002). Incorporating occupants’ thermal comfort in the control of building systems thermal environment saves heating, ventilation, and air conditioning (HVAC) energy comsumption (Erickson and Cerpa, 2012; Hang-yat and Wang, 2013; Nguyen and Aiello, 2013; Nouvel and Alessi, 2012; Purdon et al., 2013; Sarkar et al., 2016).

One challenge to non-intrusively incorporate each occupant’s feedback on the thermal environment is to accurately predict thermal comfort in the dynamic, non-uniform, and real environment. The most popular thermal comfort model, the predicted mean vote (PMV) and adaptive model, has been proved to have a low predicting power (Humphreys and Fergus Nicol, 2002; Kim et al., 2018a). The effects of individual difference in physiological, psychological, and behavioral factors are not considered in these models. Rather, a personal comfort model is a new approach to thermal comfort modeling that predicts an individual's thermal comfort response, instead of the average response of a large population (Kim et al., 2018b). Personal comfort models have a much higher predicting power than PMV and adaptive model owning to additional consideration of personal factors (Kim et al., 2018a). The models can be based on environmental parameters (e.g., air temperature, location, relative humidity) (Cheung et al., 2017), occupant feedback (e.g., online voting like Comfy) (Ghahramani et al., 2015; Kim et al., 2018a), occupant behaviour (e.g., thermostat setpoints like Nest), and physiological parameters (e.g., skin temperature, heart rate) (Chaudhuri et al., 2018; Choi and Loftness, 2012; Choi et al., 2012; Huang et al., 2015; Sim et al., 2016).

Occupants' physiological parameters could be measured by using infrared thermography (Ranjan and Scott, 2016) or wearable sensors (Ghahramani et al., 2016; Li et al., 2017a; Shen et al., 2012). The major challenges of infrared thermography and occupant behavior are either single parameter (e.g., skin temperature) tracking or difficulties in long-term monitoring in a free-living environment. Security is also a concern. By contrast, wearable sensors that are capable of measuring physiological signals and other parameters without relying on stationary infrastructure, are suitable for the prediction of personal thermal comfort in real life. Other benefits include cost, market penetration, privacy and opportunities to be infused in health monitoring. Moreover, wearable fitness trackers have become broadly available, such as Fitbit (Fitbit Inc., U.S.), Apple Watch (Apple Inc., U.S.) and Garmin (Garmin Ltd., U.S.). The emerging sensing technology provides the opportunities to apply the measured data to infer thermal comfort. For instance, wearable sensors were deployed together with in-home environmental sensors to predict thermal comfort in households (Huang et al., 2015). Occupants' real-time feedback on thermal preference was predicted by using physiological data (e.g., skin temperature, heart rate, activities) along with indoor environmental parameters (e.g., air temperature and humidity) and was incorporated into building system control, creating a human-in-the-loop system (Li et al., 2017).

Capturing the transitions among different thermal environments were found a challenge by wearable sensors. Most recent studies on applying wearable sensors to predict thermal comfort were conducted with participants restrained in a laboratory (Chaudhuri et al., 2018; Ghahramani et al., 2016; Sim et al., 2016; Sugimoto, 2013). Furthermore, occupants' diverse daily activities, such as cooking or commuting, have been rarely included in previous investigations. The feasibility and accuracy of personal thermal comfort prediction for real-life wearers are still unclear. The knowledge gap could be addressed probably only by continuously tracking occupants for a long-term.

In addition, it is worth attention that the accuracies of wearable sensors might cause uncertainties to thermal comfort inference. However, very few studies have reported the validation of sensors' measuring accuracies. In a laboratory environment, physiological signals measured and environmental data by commercially-off-the-shelf sensors were applied to train an algorithm to calculate PMV (Abdallah et al., 2016). The study pointed out that existing sensors need to be improved to increase accuracy, which was also affirmed by a recent study (Barrios and Kleiminger, 2017).

The objective of this study is to develop personal thermal comfort models using physiological and environmental data collected by wearable sensors. Compared to existing technologies, such non-intrusive solutions do not disturb occupants for survey input after personal comfort models have been trained. The models can be used for the control personal comfort systems but they can also be applied to general mechanical systems in buildings or vehicles.

2. Methodology

Different from group-average models such as the PMV and adaptive model, a personal model should be specifically developed for an occupant to account for the great variation in personal factors. Personal models might have various formats for different occupants. As such, personal models are likely inexplicitly determined using data-driven methods such as continuous training of machine learning algorithms over streaming data. Figure 1 displays the framework of personal thermal comfort modeling that can be used for building system control.

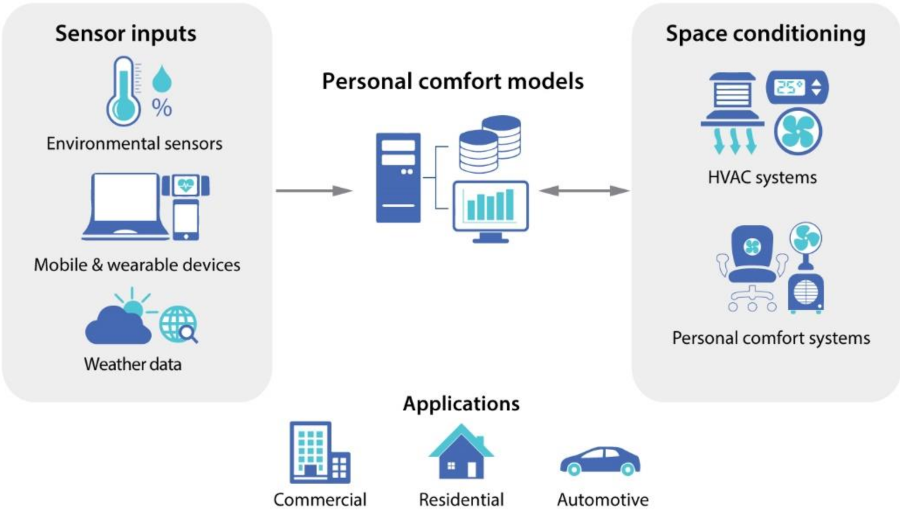

Figure 1. Framework of personal thermal comfort modelling. (Adapted from Kim et al., 2018b)

In this study, we collected and formatted physiological responses from human subjects and applied machine learning algorithms to train a personal thermal comfort model for each subject. Thermal sensation and preference data from surveys were utilized as ground truth for model development and evaluation.

2.1. Subjects

We initially recruited twenty subjects (half females and half males) from Berkeley and San Francisco through posted announcements and snowball sampling method. Most subjects were college students. The subjects were divided into four groups, A-D, corresponding to four sets of acquisition devices. The ID number in Table 1 refers to different subjects in each group. However, six of them did not complete the entire experiment that required participation for two weeks. Therefore, the final data-analysis has only considered 14 subjects (6 females and 8 males). Table 1 shows the detailed anthropometrics of the subjects.

Table 1. Anthropometrics of subjects in this study

ID	Sex	Age	Height (m)	Weight (kg)	BMI*	Sensitivity to thermal environment†	Participation time
A1	Male	26	1.71	68	23.3	3.7	Nov. 28^{th} - Dec. 12^{th}, 2016
A2	Male	25	1.85	86	25.1	2.9	Apr. 2^{nd} - 23^{th}, 2017
A4	Male	31	1.7	55	19.0	3.5	May 1^{st} - 19^{th}, 2017
A5	Female	38	1.63	54	20.3	2	May 23^{rd} - Jun. 6^{th}, 2017
B1	Male	24	1.73	52	17.4	3.5	Oct. 17^{th} - Nov.10^{th}, 2016
B3	Female	28	1.73	86	28.7	3	Dec. 5^{th} - 20^{th}, 2016
B6	Female	25	1.8	57	17.6	3.1	Apr. 5^{th} - 23^{rd}, 2017
B8	Male	23	1.75	57	18.6	4	Apr. 30^{th} - May, 17^{th}, 2017
B9	Male	21	1.81	73	22.3	3	May 19^{th} - Jun. 8^{th}, 2017
C1	Female	48	1.63	57	21.5	3.7	Mar. 21^{st} - Apr. 17^{th}, 2017
C3	Female	20	1.65	52	19.1	2.5	May 14^{th} - Jun. 28^{th}, 2017
D1	Male	21	1.75	61	19.9	3	Dec. 2^{nd} - 19^{th}, 2016
D2	Male	32	1.8	70	21.6	3	Apr. 23^{rd} - May 8^{th}, 2017
D3	Female	22	1.58	56	22.4	3	May 13^{th} - Jun. 1^{st}, 2017

*BMI: Body mass index = Weight/Height^2

† Sensitivity to thermal environment from a survey question (Please indicate how sensitive you think you are to thermal conditions): Much lower sensitivity (0); Much higher sensitivity (5).

2.2. Questionnaires

Subjects took an online survey developed on Qualtrics using a cell phone to report their "right-now" thermal comfort. To reduce fatigue due to survey taking, subjects answered only three questions each time: 1) location (indoor or outdoor); 2) thermal sensation (continuous ASHRAE thermal sensation scale from cold <-3> to hot <3>); and 3) thermal preference (warmer, no change and cooler). The questions were randomly displayed on the survey platform (Figure 2).

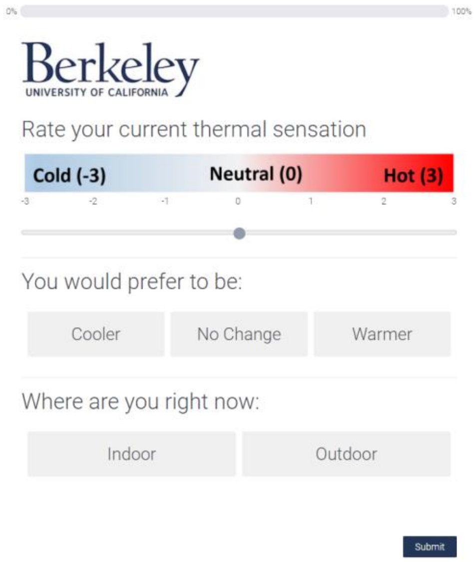

Figure 2. Online survey platform using Qualtrics

2.3. Wearable sensors

All the sensors are commercial and available on the market. The sensors were selected based on three criteria: 1) accuracy; 2) raw data access for research support; and 3) convenience to wear for 24/7. Despite that commercial wrist-bands and smart watches are easily accessible and user-friendly, the accuracy or capacity of research support fail to meet the requirements of this study. As such, all the sensors in this study were validated to generate data with accuracies of research purposes according to literature (Gillinov et al., 2017; van Marken Lichtenbelt et al., 2006; Mourcou et al., 2015). For instance, Basis Peak (Intel, Corp., U.S.) and Fitbit Charge HR (Fitbit, Inc., U.S.) inaccurately measure heart rate during exercise (Wang et al., 2017). As such, we applied Polar H7 strap (Polar Electro, Ltd., Finland) to monitor heart rate every second because of the high validity compared to ECG (Cheatham et al., 2015). Additionally, since subjects wore sensors for almost 24/7, two of the authors participated in a preliminary study for approximately two weeks to ensure that the selected sensors meet the criteria in the timeframe of participation.

Table 2 and Figure 3 describe the specification of the sensors and the wearing locations, respectively. Skin temperature at wrist and ankle was measured every minute by an iButton sensor (van Marken Lichtenbelt et al., 2006; Smith et al., 2010). In addition, we attached one iButton (Maxim Integrated Products, Inc., U.S.) sensor with the sensing side facing outside to a pin-badge to measure every minute the air temperature in the body proximity in order to capture transitions between different thermal environments. The badge was pinned at the lower pant (Figure 2) to reduce the influence of body thermal plume. Subjects took off pants with the sensor badge before sleep. The measured data represented air temperature where pants were located during sleep. A small-size cell-phone (POSH Mobile, Ltd., U.S.) in a wrist pocket measured accelerometer data to represent activity levels. The sample frequency was greater than 5 Hz, depending on the intensity of movement. Moreover, the cell-phone wirelessly uploaded heart rate data to the cloud.

Table 2. Sensors to measure physiological data

Model	Accuracy	Parameter measurement
iButton- Maxim integrated DS 1923 (Maxim Integrated Products, Inc., U.S.)	± 0.2 °C after calibration	Skin temperature and air temperature close to the body
Polar H7 Bluetooth Smart Heart Rate Sensor (Polar Electro, Ltd., Finland)	Concordance correlation coefficient, 0.99 (Wang et al. 2017)	Heart rate
Cell phone POSH built app Micro X S240 (POSH Mobile, Ltd., U.S.)	Not applicable	Accelerometer data to represent metabolic rates. Server to receive heart rate data

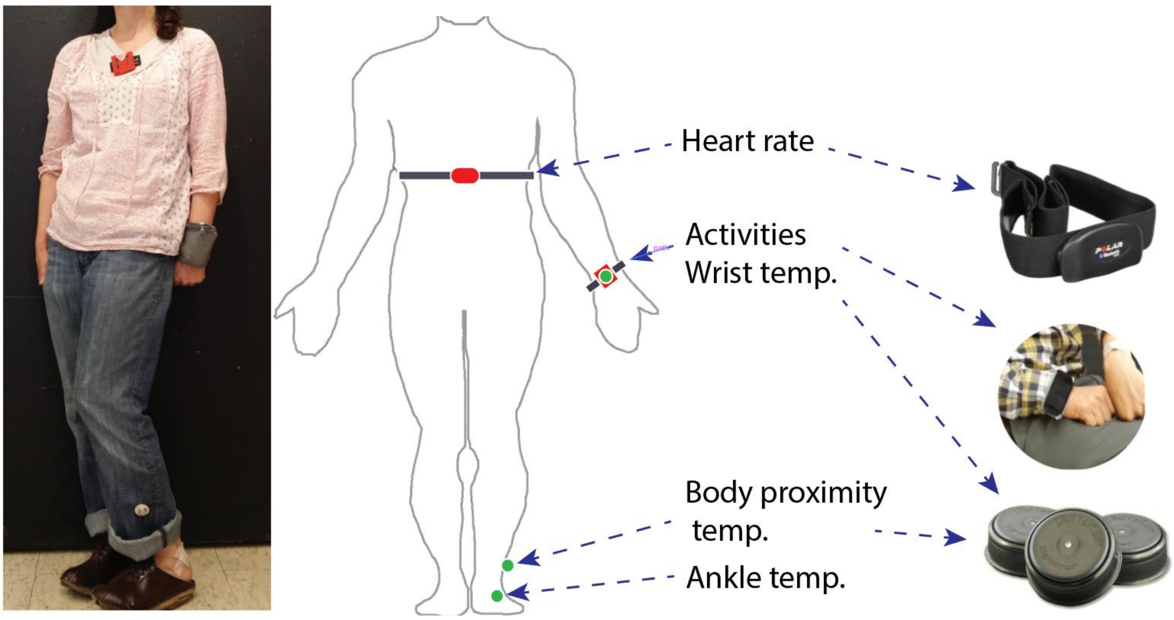

Figure 3. Sensors and wearing locations.

2.4. Procedure for data collection

Before participation, each subject had a one-hour training on the study procedure. The subjects were also asked to wear the sensors during the train to ensure that they were comfortable with them. A signed consent form approved by the institutional review board of University of California, Berkeley (CPHS #2016-09-9129) was obtained from each subject.

The subjects wore all the sensors for at least 20 hr and took the survey (Figure 2) for at least 12 times per day. The total duration of the participation was 14 days. We encouraged subjects to take the survey as many times as possible, especially when their thermal conditions and preferences altered, such as after working out or moving to a different thermal environment. The subjects received a text reminder to take the survey. Each subject was compensated with $350 (or more if taking more surveys) after the entire participation.

Table 2. Parameters and features for the development of personal thermal comfort models

Parameters	Features
Skin temperature at ankle and wrist	Temperature gradient over 15 min before a vote
	Average temperature over 15 min before a vote
	Temperature gradient over 60 min before a vote
	Average temperature over 60 min before a vote
	Temperature difference between daily average and 15 min average before a vote
	Average skin temperature difference between wrist and ankle over 15 min before a vote
	Difference between daily average outdoor and skin temperature averaged over 15 min before a vote
Body proximity temperature	Temperature gradient over 15 min before a vote
	Average temperature over 15 min before a vote
	Temperature gradient over 60 min before a vote
	Average temperature over 60 min before a vote
	Temperature difference between daily average and 15 min average before a vote
	Difference between daily average outdoor and body proximity temperature averaged over 15 min before a vote
Heart rate	Difference between daily and 15 min average before a vote
	Difference between daily and 60 min average before a vote
Metabolism	Variation of accelerometer data over 15 min before a vote
	Variation of accelerometer data over 60 min before a vote
Location	Indoor or outdoor
Time	Morning (0 - 12:00), afternoon (12:00 - 18:00), or evening (18:00 - 24:00)
Weather	Average outdoor temperature, humidity, wind, and precipitation over 60 min before a vote

2.5. Machine learning algorithm and feature selection

Among the three surveyed questions (Figure 2), thermal preference is the most relevant parameter to HVAC system control because it explicitly describes which action the HVAC should take. This study aims to apply classification algorithms to develop a thermal comfort model for each subject to infer their thermal preference.

Random Forest (RF) constructs a multitude of individual decision trees and predict mean outcomes from the average results of all the trees (Breiman, 2001). This technique, also known as “bagging”, is particularly powerful in the small data regime, because it effectively generates an “artificial” dataset for each individual learner based only on the limited available data (Breiman, 1996). Random Forest has been successfully applied for thermal preference classification (Huang et al., 2015).

The features for model training consisted of physiological data, body-proximity temperature, weather (wind, solar radiation, temperature, humidity), location and time (Table 2). The derivatives (e.g., gradients and standard deviation) of the measured data were also considered. For instance, the negative gradient of skin temperatures of the extremities represented the drop of skin temperature, possibly indicating a cool thermal sensation (Wang et al., 2007).

3. Results and Discussion

3.1. Thermal sensation and preference

The overall thermal sensation and preference of each unique subject are shown in Figure 4. The vote number during the entire participation was 275 ± 77 (mean ± standard deviation). Most of the thermal sensation votes (interquartile range) were between slightly cool and slightly warm. The mean thermal sensation for all subjects is close to neutrality (mean ± standard deviation: 0.06 ± 0.75). However, thermal sensation ranges are significantly different among subjects. For instance, the thermal sensation range of subject B1 (0.44 ± 1.16) was much smaller compared to subject B8 (0.33 ± 0.05).

The subjects in this study preferred changing their thermal environment for about 30% (min = 21% and max = 88%) of the participation period, which suggests a strong demand for a personalized thermal comfort.

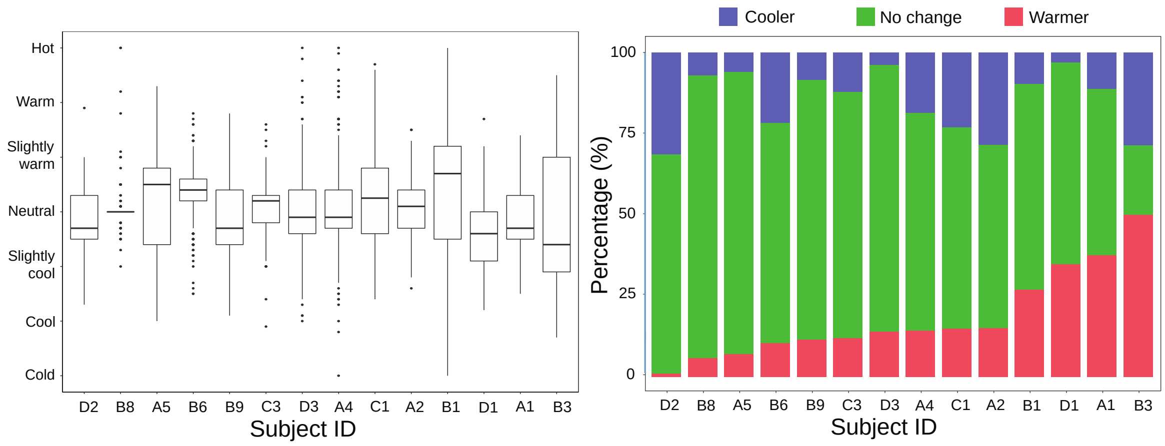

Figure 4. Thermal sensation and preference for each subject

3.2. Thermal preference prediction

We trained a personal comfort model with thermal preference as the dependent for each subject. Table 3 summaries the overall classification of warmer, no change and cooler. The accuracy was calculated as the chance (in percentage) of predicting a thermal vote correctly. The average accuracy of all the subjects is 74 ± 13% (mean ± standard deviation) for the field experiments. It is worthy to notice that the accuracy increase with the increase of the data size, above 300 votes, the accuracy is on average 80%. The differences in the accuracies imply that the dominant features to predict thermal preference might be different for each subject. A further investigation on the contribution of each feature to the prediction accuracy is underway.

Table 3. Overall classification of warmer (W), no change (NC) and cooler (C) for each subject

ID	Data size	True preference: Warmer			True preference: No change			True preference: Cooler			Overall accuracy (%)
		W*	NC*	C*	W*	NC*	C*	W*	NC*	C*	
A1	152	**28**	29	0	27	**51**	0	5	10	**2**	53
B3	242	**98**	8	15	41	**8**	3	40	3	**26**	55
A2	253	**2**	36	0	1	**126**	16	0	54	**18**	58
D1	156	**15**	37	0	13	**86**	0	0	3	**2**	66
C1	256	**11**	26	1	12	**136**	11	2	34	**23**	66
B1	271	**16**	57	0	9	**160**	3	1	18	**7**	68
B6	393	**2**	39	0	0	**264**	3	0	77	**8**	70
B9	261	**10**	20	0	9	**197**	3	0	19	**3**	81
C3	399	**14**	34	0	5	**295**	3	0	35	**13**	81
D2	198	**0**	2	0	0	**129**	5	0	24	**38**	84
A5	270	**0**	19	0	1	**232**	2	0	16	**0**	86
D3	322	**12**	33	0	0	**265**	0	0	9	**3**	87
A4	323	**13**	28	5	2	**215**	0	1	1	**58**	89
B8	353	**9**	12	0	2	**304**	1	0	9	**16**	93

*Predicted thermal preference: Warmer (W); No change (NC); Cooler (C)

In this study, the thermal comfort learning method based on Random Forest requires the collection of a sufficiently large labelled dataset for representation of common scenarios and generalization to unknown situations. This poses a practical challenge, because people may be reluctant to report their thermal comfort due to weariness. The authors will be developing data-efficient algorithms that alleviate this stringent requirement. One promising direction is to train the classifiers with high-level heuristic rules rather than low-level labels, a form known as "weak supervision" (Jin, 2017). The idea has been applied to occupancy detection based on smart meter data by leveraging common work schedules (Jin et al., 2017). Similarly, for thermal comfort, heuristics such as "I typically feel cold at night" or "I usually feel hot after running" can be readily encoded into noisy estimates of thermal comfort labels to initiate weakly supervised learning. This can potentially enable large-scale deployment of the proposed method of thermal comfort sensing.

4. Conclusions

We used wearable sensors to track real-time physiological signals and environmental data for almost 24/7 for each subject. The collected information was trained by a Random Forest algorithm to develop personal thermal comfort model. The subjects' perceived thermal comfort was also recorded as ground true for the model development and validation. We are able to predict personal thermal preference with an average accuracy of 75% (53 - 93%) based on physiological signals (skin temperatures at wrist and ankle, heart rates, and activity levels) and environmental data. The results imply that wearable sensors can be suitable tools to infer thermal comfort in the free-living environment. In the future, we will explore more features from the sample data and more robust algorithms to reduce the requirement of survey inputs during the training period.

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