Understanding the Influence of Short-Term Thermal History on Personalized Thermal Comfort Votes

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Abstract

Recent studies have investigated personalized thermal comfort modeling using probabilistic and machine-learning-based techniques to enhance the capability of contextualizing human factors for building systems' operation and simulation. Different modeling schemes and input parameters have been used to create models with varying degrees of accuracy. Inspired by the thermal acclimation process, we have investigated the influence of short-term thermal history on individuals' thermal comfort votes as a critical variable in the modeling process. To this end, through an experimental study in a controlled environment, 10 human subjects were exposed to two consecutive modes of thermal conditioning with transient temperature configurations – gradually changing from low to high and then high to low temperatures while collecting environmental and human-related data. Through statistical analyses, it was observed that the temperature ranges, for which participants reported thermal comfort satisfaction were significantly different depending on the conditioning modes. Moreover, participants showed to have different sensitivities (reflected in rates of providing response) in these consecutive conditioning modes. These preliminary findings provide an insight into the necessity of tracking short-term thermal history for personalized thermal comfort modeling to enhance control and simulation processes for energy efficiency.

Introduction

Contextualizing indoor condition requirements associated with occupants' personal thermal comfort via participatory sensing has been demonstrated as a potential way to integrate dynamics of human factors in the operation of Heating, Ventilation, Air-Conditioning (HVAC) systems (Pritoni, Salmon et al. 2017). It has been shown that such an approach prevents over-conditioning (Jazizadeh, Ghahramani et al. 2013), helps identify the ranges of acceptable conditions allowing building systems to reduce conditioning loads (Purdon, Kusy et al. 2013, Jung and Jazizadeh 2020), and improves occupants' comfort (Erickson and Cerpa 2012). This approach has been defined as comfort-aware operations that rely on personalized thermal comfort modeling using probabilistic or machine-learning-based methods. Therefore, thermal comfort votes either as thermal sensation/perception or preference is an important variable in the modeling process.

However, owing to the subjective nature of thermal comfort as shown in Figure 1, variations of votes reported under the same environmental conditions complicate the process of inferring individual comfort characteristic patterns and limit the potentials of comfort-aware HVAC operations. This approach requires precise prediction of occupant thermal comfort to enable energy-efficient adjustment of indoor conditions. As synthesized in our recent review article (Jung and Jazizadeh 2019), the accuracy of predicting individual comfort without using any physiological parameters as input into machine-learning algorithms was reported to be between 60 – 70%.

In field studies, it has been shown that temperature is the main driving factor with a dominant impact on thermal comfort vote variations (Jazizadeh, Marin et al. 2013). Therefore, in comfort-aware operations, when occupants provide or change their votes, the corresponding ambient temperature is captured and used in developing personalized comfort profiles. However, as noted, given the fact that thermal acclimation property and the short-term thermal history could affect individual comfort perceptions, in this study, we have investigated the impact of this factor on votes reported by human subjects. The findings will provide an insight into considerations for data collection and modeling of personalized comfort predictors.

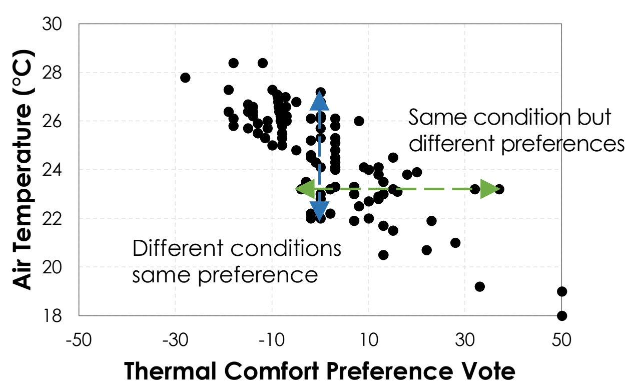

Figure 1. Dynamic and inconsistent nature of thermal votes (Jazizadeh, Ghahramani et al. 2014)

According to the American Society of Heating, Refrigerating, and Air-conditioning Engineers (ASHRAE), thermal perceptions could vary across different seasons. Occupants' thermal satisfaction could be affected by seasonal variations in outdoor temperatures. Adjustments in clothing values provide an opportunity in each season to apply different temperature setpoints, which could adjust the required conditioning load by HVAC systems and even improve efficiency (Erickson, Carreira-Perpiñán et al. 2011, Erickson, Achleitner et al. 2013). In addition to those seasonal variations in occupants' thermal experiences, short-term thermal history, and its corresponding physiological acclimation could affect the occupant experience and their temporal perception of the indoor ambient conditions. Therefore, in this study, we have focused on this aspect. In doing so, we have performed an experimental study by including 10 participants using a thermal conditioning strategy that provides a change in participants' short-term thermal history. Participants' votes were collected by utilizing a thermal preference scale indicating whether a participant is comfortable, desires a lower temperature (uncomfortably cool), or desires a higher temperature (uncomfortably warm).

In the remaining sections of this paper, we have presented a background of recent studies on comfort-aware operations for HVAC systems and the commonly used variables for personalized comfort modeling, as well as the experimental and analytical methods, followed by the findings.

Comfort-Aware Operations Paradigm

Under the premise that user-adjusted temperature setpoints (hereinafter setpoints) provide satisfactory indoor conditions, HVAC systems use thermostats in the control loop. To identify the setpoints, generalized recommendations or standard models such as predicted mean vote (PMV) are used. In other words, the HVAC systems condition the space under the assumption that most occupants will be satisfied by using those operational setpoints. Considering the feasibility of using generalized setpoints for thermostats, they have been commonly used in practice, and in some occasions, questionnaires have been used to collect occupants' thermal comfort perceptions (Huizenga, Laeser et al. 2002). However, discrepancies between actual votes and PMV values have been reported in different studies (Hoof 2008, Becker and Paciuk 2009). The generalization of human-related parameters, such as the metabolic rate, is one of the major causes of such discrepancies (Hoof 2008). Therefore, standardized methods could be improved to better contextualize how individual occupants perceive the environment as satisfactory.

Benefiting from ubiquitous computing technologies, participatory sensing through web- or smartphone-based surveys has paved the way for contextualizing human factors in regard to individual's thermal comfort. This approach has gained attention by researchers in the wake of emphasizing the personalization of comfort assessments (Humphreys and Hancock 2007). This paradigm of the HVAC operations is, as noted, called comfort-aware HVAC operations.

At the inception of this new paradigm, studies employed real-time votes to identify optimal setpoints in multi-occupancy spaces (Murakami, Terano et al. 2007, Purdon, Kusy et al. 2013). Later, with the aim of reducing the required level of user intervention, studies sought methodologies to benefit from pattern recognition for individuals' thermal comfort profiling based on a set of previously collected votes using cutting-edge machine-learning algorithms (Daum, Haldi et al. 2011, Li, Menassa et al. 2017). In other words, personalized predictive models of thermal comfort are developed to enable a mapping between indoor ambient conditions and occupants' experience.

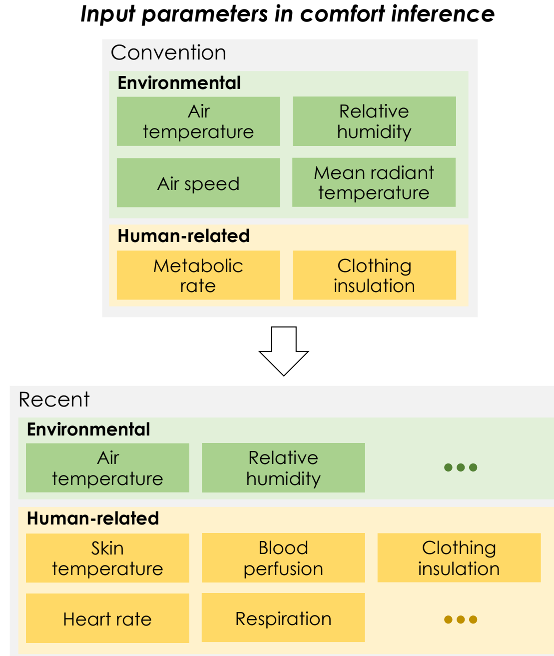

Figure 2. Variations of input parameters in prediction of thermal comfort due to the shift of the paradigm from generalization to personalization

The conventional input parameters in the prediction of thermal comfort are air temperature, relative humidity, air speed, mean radiant temperature, metabolic rate, and clothing insulation as employed in the PMV model. On the other hand, in recent years, as indicated in Figure 2, studies have used or proposed different input parameters by considering the trade-off between the need for user engagement versus feasibility of advanced sensing methodologies (Jung and Jazizadeh 2017, Jung and Jazizadeh 2018, Li, Menassa et al. 2018). For example, the need for a total of 27 parameters (according to ASHRAE) to measure the actual metabolic rate could be relaxed by acquiring some of the physiological responses of the human body through novel physiological sensing systems (Jung and Jazizadeh 2018). These research efforts have contributed to improving the performance of thermal comfort inference. However, they have not investigated the impact of short-term thermal history.

Despite the active exploration of human-related parameters in recent years (Jung and Jazizadeh 2019), studies have relied on a limited number of environmental parameters by disregarding parameters, such as air speed and mean radiant temperature. The reason could be twofold: (1) the similarity of the mean radiant temperature to air temperature in most conditions (Walikewitz, Jänicke et al. 2015) and (2) the complexity of measuring air-speed and generalized recommendations by standards – ASHRAE has recommended the average air speed of 0.20 m/s at the location of occupants as a limit in thermal comfort satisfaction (ASHRAE 2017).

While studies have recommended different combinations of ambient and human-related variables for personalized thermal comfort models, variations in ambient temperature have a high correlation with changes in thermal votes (Jazizadeh, Marin et al. 2013). This is not only related to instantaneous temperature measurements, but it could be associated with the short-term thermal history that we have investigated in this study. It is worth noting that thermal history is a parameter that could be conveniently quantified by tracking the temporal temperature variations.

Methodology

An experimental study was designed and conducted upon receiving the approval of Virginia Tech's Internal Review Board (IRB). An isolated testbed was used as a thermal chamber for the experiment. To simulate the transient thermal conditions, we employed gradually increasing and decreasing transient temperatures, which represent heating and cooling modes, using an air-conditioning unit only for control of the ambient temperature. To minimize the impact of the radiant heat exchange, the selected testbed was a space with no windows. As illustrated in Figure 3, human subjects were positioned so that they were not directly affected by the jet of the conditioned air. By configuring the testbed in this way, our objective was to allow a slow temperature variation with small steps at a time.

In total, 6 males and 4 females participated in the experiments for this study. We asked participants to wear short-sleeved t-shirts and long pants (around 0.5 clo) to minimize the impact of the clothing insulation variable. All participants declared that they were healthy prior to the experiments. After meeting these criteria, we conducted the experimental study following the procedure described below.

(1) Each participant waited for 10 – 15 minutes outside the thermal chamber in the building (around 22°C) to stabilize his/her metabolism and go through the temperature acclimation process. This is because walking from outside could increase metabolism and the subject might experience a considerable temperature change once he/she enters the thermal chamber.

(2) The thermal chamber was initially conditioned at around 20°C and each participant experienced this condition for five minutes prior to the start of the experiment.

(3) Throughout the experiment, the temperature and humidity were continuously measured using a sensor system with a sampling frequenting of 0.5Hz. Participants reported their thermal preference using an 11-point scale from -5 (desire for a lower temperature) to 5 (desire for a higher temperature). To ensure consistency of thermal comfort votes, a thermal preference scale that we have designed for this purpose (Jazizadeh, Marin et al. 2013) was used.

(4) The temperature was adjusted at a pace of around 1ºC per 5 minutes.

(5) The participants experienced a temperature increase from around 20°C (68°F) to around 28°C (86°F) and then a temperature decrease from around 28°C to around 20°C. The total duration of each experiment was 65 – 90 minutes.

(6) The participants were instructed to report their thermal preference vote every time they perceived a change in their vote.

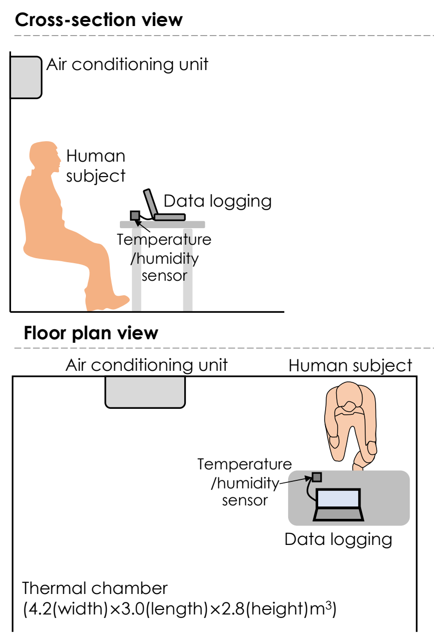

Figure 3. Cross-section and floor-plan views of the experimental testbed.

The key design point in this experimental study is step #5, during which participants experience gradually varying temperatures and develop a short-term thermal history. Participants were exposed to two transient temperature configurations in a sequence to evaluate the differences in their thermal comfort perceptions.

Data Processing and Analytics

Our objective was to show that the short-term thermal history of participants can affect their perceived thermal comfort and their thermal comfort votes. Therefore, our specific analytical objectives included:

1. Identifying the statistical difference in temperature distributions when participants felt

comfortable in different modes of thermal conditioning – i.e., heating and cooling,

2. Quantifying the variations of thermal preference votes with respect to temperature variations over time in different modes of thermal conditioning i.e., heating and cooling.

Even though we collected the relative humidity data throughout each experiment, given its marginal impact on thermal comfort (Jazizadeh, Marin et al. 2013), we focused our analyses on air temperature. However, it is worth noting that the relative humidity was from 20.3% to 48.4% throughout the experiments and none of the participants directly complained about humidity. For our first analytical objective, to evaluate the statistical difference in temperature ranges that resulted in thermal satisfaction votes, we sampled the participants' thermal votes every two seconds and matched them with the air temperature data. For instance, when a participant reported a vote of zero (reflecting thermal satisfaction and preference for no change) at 10:05 am and changed it to a negative vote (reflecting a preference for a cooler environment) at 10:15 am, participant's votes during this 10-minute interval were sampled to be zero. We created two datasets representing each one of the thermal conditioning modes. For the statistical comparisons, we performed Welch's t-test between two datasets.

The Welch's t-test applies to the cases having samples with unequal sample sizes and variances. In our cases, participants often reported comfort across different lengths of time for the two scenarios. Note that given its strength in Type I error (the rejection of a true null hypothesis; so-called false positive), the use of the Welch's t-test is recommended when two sample sizes are different (Ruxton 2006, Derrick, Toher et al. 2016). Different from the Student t-test that assumes the same variance for the populations, the calculation of a test statistic (t') is presented in Equation (1).

$$t' = \frac{\mu_1 - \mu_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{1}$$

where 1 and 2 represent each group, μ is the mean, s^2 is the variance, and n is the sample size. The degree of freedom (v) is calculated as reflected in Equation (2).

$$v = \frac{\left(\frac{1}{n_1} + \frac{u}{n_2}\right)^2}{\frac{1}{n_1^2(n_1-1)} + \frac{u^2}{n_2^2(n_2-1)}} \tag{2}$$

where u is s_2^2/s_1^2 . Using the values from the above equations, we evaluated the null hypothesis and calculated the p-values.

For our second analytical objective, we quantified the variations of thermal votes with respect to temperature variations over time in each mode of thermal conditioning. In other words, we evaluated each participant's tendency for utilizing the thermal preference scale to report a preferred change with respect to temperature variations. In doing so, we used the metrics presented in Equation (3).

$$TVCR = \frac{|T_{gap}|}{|TV_{gap}|} \tag{3}$$

where $TVCR$ refers to Thermal Vote Change Rate, T_{gap} is the gap between the initial and end temperatures, and TV_{gap} refers to the gap between the initial and end thermal votes.

Results

Figure 4 presents example graphs of measurements for one participant. In general, participants showed expected responses to temperature variations. When the temperature was increasing, they reported preferences for having lower temperatures by using negative votes and vice versa. However, as Figure 4 shows, the noticeable difference was between air temperature ranges, for which the participants reported a vote of zero, reflecting thermal comfort satisfaction in each thermal conditioning mode. As shown in Table 1, not only the mean values were different, but also the p-values of two datasets from Welch's t-test indicated that they were statistically significantly different with p-values of less than 0.01 for all participants. Prior to using Welch's t-test, we confirmed that the two datasets had different variances and numbers of samples, which justified the use of Welch's t-test.

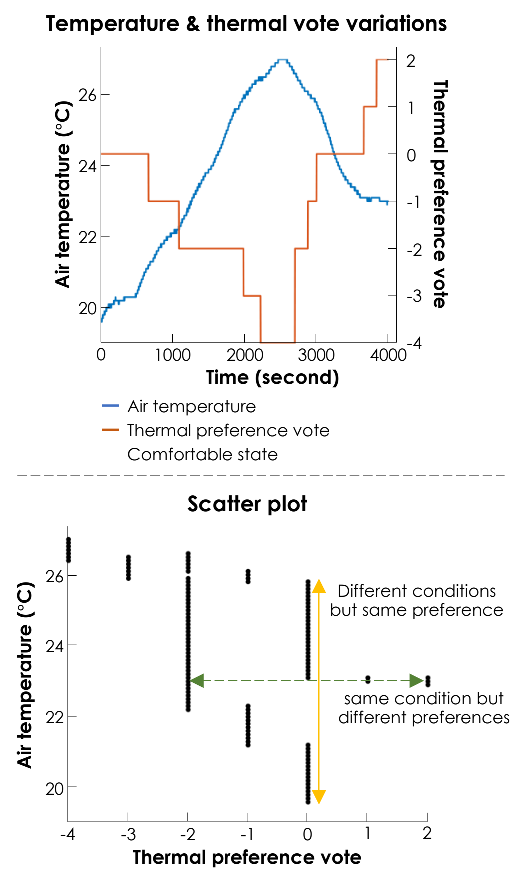

Figure 4. Observations for human subject #10.

Table 1. Mean and variance of the temperatures and the length of time when each participant felt comfortable in heating and cooling modes and the corresponding p-values from Welch's t-test.

Subject	Mean temperature while comfortable (°C)		Variance of the temperature while comfortable (°C)		Length of time being comfortable (minutes)		P-value from Welch's t-test
	Heating	Cooling	Heating	Cooling	Heating	Cooling	
1	22.9	25.9	0.190	0.153	3	3	<0.01
2	23.4	24.8	0.285	1.046	7	20	<0.01
3	22.6	26.1	2.007	0.316	23	7	<0.01
4	20.6	25.8	0.477	0.324	9	4	<0.01
5	20.6	25.0	0.288	0.045	10	3	<0.01
6	22.4	24.0	1.956	0.932	27	24	<0.01
7	21.4	23.2	0.103	0.451	4	14	<0.01
8	22.8	25.6	0.142	0.114	8	8	<0.01
9	21.1	24.3	0.061	0.372	8	9	<0.01
10	20.4	24.1	0.182	0.729	11	11	<0.01

Table 2. Thermal sensitivity of each subject in the heating and cooling modes.

Subject	Heating					Cooling				
	Vote		Temperature (°C)		Thermal vote change rate (°C/Vote)	Vote		Temperature (°C)		Thermal vote change rate (°C/Vote)
	Initial	End	Initial	End		Initial	End	Initial	End	
1	3	-5	17.1	29.3	1.525	-5	5	29.3	19.1	1.020
2	3	-5	19.9	30.0	1.263	-5	4	30.0	21.7	0.922
3	0	-5	20.4	29.2	1.760	-5	4	29.2	22.1	0.789
4	1	-4	18.9	29.4	2.100	-4	3	29.4	21.1	1.186
5	0	-5	19.6	28.4	1.670	-5	4	28.4	21.0	0.822
6	0	-4	19.9	27.6	1.925	-4	1	27.6	22.9	0.940
7	2	-5	20.4	27.1	0.957	-5	2	27.1	22.0	0.729
8	1	-5	21.1	26.8	0.570	-5	5	26.8	23.6	0.320
9	0	-3	20.6	27.6	2.333	-3	1	27.6	23.3	1.075
10	0	-4	19.6	27.0	1.850	-4	2	27.0	22.9	0.683
Average	1	-4.5	19.75	28.24	1.6	-4.5	3.1	28.24	21.97	0.85

In addition, although this study used an experimental setup with controlled temperature variations in contrast to the field study by Jazizadeh, Ghahramani et al. (2014), the scatter plot in Figure 4 manifests similar patterns that can be observed in Figure 1 – i.e., different indoor thermal conditions with same thermal preferences (blow line) and same conditions with different thermal preferences (green dashed line). These observations show that the thermal votes reported by users could be affected by their short-term history of thermal experience. Therefore, the record of an air temperature at the time of reporting thermal votes might not fully represent the context in determining thermal comfort perceptions.

The observations could be interpreted that the order of conditioning, from heating to cooling, showed to have an impact on participants' perceptions. Most of the participants reported to be comfortable at around 20.0 to 23.0°C, and the temperature was increased at least by 4.0°C more. When the cooling mode started, participants were relieved by the fact that the temperature was reduced in the testbed. In other words, their bodies had been acclimated to the heating mode and then the cooling mode started, causing a sensory differential and a feeling of relief that resulted in thermal comfort satisfaction at different temperature ranges. With respect to the rates of change in thermal votes, as shown in Table 2, all participants were more sensitive to the second part of the experiments when the air temperature was decreasing. This sensitivity is reflected in the fact that the average TVCR is higher for the heating mode. This could be also related to participants' acclimation over time after fading of the initial relief, which resulted in voting in response to the short-term history of the thermal condition.

Conclusion

Seeking to understand the impact of short-term thermal history on thermal comfort preference votes, in this study, we conducted an experiment with 10 human subjects. The results showed that the thermal history could play an important role in driving thermal comfort votes. Short-term thermal history resulted in significant differences in temperature ranges for the same thermal comfort votes. Therefore, it should be considered as an environmental parameter for personalized thermal comfort inference and comfort-aware HVAC operations. All subjects felt comfortable at a different temperature range for consecutive heating and cooling modes. Another key observation was that the subjects were more sensitive to the cooling mode, compared to the heating mode considering that on average it took smaller changes in temperature for them to report a change in their preference. This could be associated with the fact that the changes in the votes are driven by indoor temperature differentials. Once the initial relief of running the cooling mode faded away, acclimation to new conditions resulted in more frequent votes.

There are limitations in this preliminary study that should be addressed in future explorations: (1) the order of the conditioning modes may have an impact on the observations; (2) the testbed was a closed controlled space without any windows, but more complex heat exchange mechanisms could be observed in actual indoor environments; (3) more complex measurements could reveal more information on the causation of the observed variations on thermal experiences. To further explore the influence of thermal conditioning modes and short-term thermal history on thermal comfort votes, future studies beyond this preliminary exploration are needed. Training of personalized thermal comfort inference models could be conducted by integrating thermal history features to evaluate their impact on model performance improvement. Moreover, field studies could be conducted to assess the feasibility of addressing thermal history in the operation of comfort-aware HVAC operations.

Acknowledgment

This material is based upon work supported by the National Science Foundation under grant #1663513. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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