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Towards unsupervised learning of thermal comfort using infrared thermography

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HIGHLIGHTS

- A non-contact and non-invasive data acquisition method via infrared thermography was utilized.
- A hidden Markov model learning approach is introduced to capture dynamic thermal comfort.
- Comfort is achieved via preventing existence of uncomfortable conditions as a logical inference.
- 82.8% of prediction accuracy for detection uncomfortable conditions was obtained.
- Generalizing hyper-parameters of the model enables unsupervised learning of thermal comfort.

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ABSTRACT

Maintaining thermal comfort in built environments is important for occupant health, well-being, and productivity, and also for efficient HVAC system operations. Most of the existing personal thermal comfort learning methods require occupants to provide feedback via a survey to label the monitored environmental or physiological conditions in order to train the prediction models. Accuracy of these models usually drops after the training process as personal thermal comfort is dynamic and changes over time due to climatic variations and/or acclimation. In this paper, we present a hidden Markov model (HMM) based learning method to capture personal thermal comfort using infrared thermography of the human face. We chose human face since its blood vessels has a higher density and it is not covered while performing regular activities in built environments. The learning algorithm has 3 hidden states (i.e., uncomfortably warm, comfortable, uncomfortably cool) and uses discretization for forming the observed states from the continuous infrared measurements. The approach can potentially be used for continuous monitoring of thermal comfort to capture the variations over time. We tested and validated the method in a four-day long experiment with 10 subjects and demonstrated an accuracy of 82.8% for predicting uncomfortable conditions.

1. Introduction

Buildings account for about 30% of the total energy consumption in the world [1] (50% of which is associated with HVAC systems) and substantially contribute to the climate change (i.e., 30% of the global greenhouse gas emissions [2]). Heating, Ventilation, and Air Conditioning (HVAC) systems, responsible for providing thermal comfort in buildings, often use time-invariant setpoints derived from thermal comfort standards, such as the ASHRAE Standard 55 [3]. In several cases, this reliance on time-invariant setpoints has caused HVAC systems not to perform as desired, causing inefficiencies [4,5]. More recent models (e.g., adaptive models) account for climate variations for estimating occupants' thermal sensations [6]. However, prior research demonstrated that existing thermal comfort models do not account for several influential static and dynamic factors [4]. Static factors (e.g., race, gender [7]) are time-invariant across individuals, while dynamic factors (e.g., acclimation, age, and food intake [8–12]) make thermal comfort dynamic over time [13]. Although the impact of static factors on thermal comfort might be quantifiable through extensive and exhaustive field experiments, it is not trivial to quantify and learn the impact of dynamic factors. Lack of real-time access to building occupants' thermal comfort prevents control strategies to select temperature

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setpoints, which are more energy efficient. Potential savings of using comfort-driven and energy-aware set points vary based on the building size, type, construction materials, and climate in the range of 4–32% [14,15].

The inability of existing thermal comfort models to accurately estimate dynamic personal thermal preferences has led the researchers to explore various real-time thermal comfort sensing methods that are feasible to be used in buildings. Thermal comfort is defined as the condition of mind that expresses satisfaction with a thermal environment [16]. Consequently, thermal comfort can be measured directly only by surveying individuals about their comfort. Existing research and industry efforts to capture personal thermal comfort requires occupants to continuously provide feedback via surveys (e.g., surveys delivered through web interfaces [17]). Survey based methods are aimed to directly collect thermal preferences of occupants and consequently require the individuals to continuously answer questionnaires about their thermal comfort levels. Due to the advancements in participatory sensing methods, occupants can provide thermal comfort feedback via a web interface or an app to make the surrounding thermal environment comfortable. Evidently, survey based models identify comfort levels more accurately than the environmental and physiological measurement based models as they try to directly extract the “state of mind” of a person, however, they require continuous and frequent user feedback. Since it is impractical to continuously query occupants for their states of comfort, researchers have focused on environmental measurement based methods that aim to use training labels to correlate thermal comfort states (through continuous occupancy feedback) with environmental measurements (e.g., indoor air temperature). However, sensor and occupant locations in a built environment, as well as the size/volume of an environment make the trained models difficult to generalize. Moreover, methods based on the measurements of environmental factors do not take into account time-dependent variations into consideration unless continuous occupant feedback is provided. A comprehensive review of the two group of methods can be found in our earlier publication [18].

To reduce or ultimately eliminate the need for continuous feedback requirements for training of personal comfort models, physiological responses (e.g., skin temperature, heart rate, core temperature [19,20]) could be used to learn comfort. Physiological measurement based approaches are built upon the principle that physiological responses can be correlated with thermal discomfort. In other words, comfort is potentially maintained if no uncomfortable conditions occur. Hence, correlating the monitored measurements with occupant feedback enables predictive models to estimate an occupant’s probability of discomfort. For example, the authors of [21] introduced a data driven predictive method that integrates personalized factors with a generalized model of the body heat balance. The model coefficients were calculated dynamically based on comfort votes via minimizing an error function (i.e., least square) of coefficients. Since the data collection was done on a daily basis, the authors argued that the modeling account for time variations of comfort. In [22], a deep artificial neural network (ANN) learning technique was used for classifying environmental conditions into three categories: comfortable, uncomfortably warm, and uncomfortably cool. The ANN algorithm had 4 input layers (i.e., air temperature, radiant temperature, air flow, air humidity) and 5 hidden layers. The algorithm was trained with the comfort votes of the test subjects under controlled experiments. However, the time dependent variations of thermal comfort were not included in the study. The authors of [23] developed a heuristic based method, which relates occupants’ thermal sensations with body exergy usage rate. Their results showed that both the radiative and convective heat exchanges between an environment and a human body are satisfactory measures of body exergy usage rate. Time dependent variations were assumed to be inherently integrated in the exergy.

An adaptive thermal comfort modeling technique, which used the PMV (predictive mean vote) model as a prior model, was introduced in [24]. The model calculated an adaptation coefficient, which decreased or increased the estimated PMV values. The adaptation coefficient was calculated based on a field study that took into account local climate, culture, and social backgrounds. In [25], the authors developed an adaptive fuzzy-logic based algorithm that learns comfort on-line, using individuals’ actions on thermostats and environmental conditions. The fuzzy sets were aligned with the desired changes to the thermostat. A multiple regression model that takes mean skin temperature and its time differential as input and predicts transient thermal sensations was introduced in [20]. The results showed strong correlations (with 0.8 as correlation coefficient) for the proposed technique for predicting the sensations. The authors in [26] explored the applicability of using heart rate variability (HRV) index and the electroencephalograph (EEG) as an indicator of thermal comfort. They carried out experiments to investigate how environmental temperature influences the HRV and EEG of people and relate the two factors with the thermal comfort. They found that HRV index may be closely related to thermal comfort sensations. However, their EEG analysis demonstrated that although there could be a relationship between comfort and the measurements, future research is required to make use of the EEG measurements. In [27], authors presented a mathematical model of thermal sensation based on the neurophysiology of thermal reception. Experimental data from 12 subjects were used to develop the model and 8 subjects to validate it. The collected data included skin and core temperature measurements. For the development dataset, 12 young adult males were exposed to transient conditions where air temperature varied from 30 to 20 to 35 to 30 °C. For validation, 8 young adult males were exposed to relatively different transient conditions where air temperature varied from 17 to 25 to 17 °C. The predictive model had a mean r-squared error of 0.89 for the training stage and the relatively low mean r-squared error of 0.38.

The majority of the models mentioned above require the occupants to continuously provide feedback to train the predictive model. In other words, occupants are responsible for training the learning model to adapt to their thermal preferences. Thus, there is a need for a data collection technique that enables unsupervised personal thermal comfort learning techniques. Moreover, current physiological based methods require the sensing system to be directly connected or inserted into the human body. To be practical and adapted widely by building occupants, this modeling technique should be built using the data collected by a non-invasive sensing technique. Providing real-time personal thermal comfort information to HVAC controllers could enable designing new optimization and control paradigms that select more energy efficient setpoints while ensuring occupants’ comfort.

One of the responses of human body to thermal stress (i.e., heat or cold) relates to cutaneous vessels. The sympathetic neural control of skin blood flow includes the noradrenergic vasoconstrictor system and cholinergic active vasodilator system [28,29]. Accordingly, thermoregulation system alters heat exchange with the environment by modifying the skin blood flow through cutaneous arterioles and veins [30]. Distribution of cutaneous vessels is not uniform across a human body. On areas around the human face, the density of vessels is considerably higher [30], enabling higher blood circulation. In addition, human face is usually not covered by clothing in buildings therefore infrared radiation on a human face could be monitored easily. Therefore, in this paper, we used facial skin temperature as a measure of skin blood flow to characterize the thermoregulation responses of human body to hot and cold stresses. We specifically focused on four points on face (i.e., ear, nose, front face, and cheekbone) as they are located on different cardiovascular territories [30] and behave differently under hot or cold thermal stimuli [31]. By monitoring the thermoregulation performance, we aim to identify the thermoneutral zone and consequently predict thermal comfort. There are several methods for measuring skin blood flow, including venous occlusion plethysmography, Doppler ultrasound, laser Doppler, thermostrom, photoelectric plethysmography, impedance and radioactive isotopes [32–34]. Even though these methods have shown promising results for monitoring skin blood flow,