Feasibility Assessment of Heat Flux Sensors for Human-in-the-Loop HVAC Operations

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ABSTRACT

This study seeks to evaluate the applicability of heat flux sensors, as a proxy for contextual thermal comfort representation in an environment, for the human-in-the-loop (HITL) heating, ventilation, and air conditioning (HVAC) operations. In accounting for personalized thermal comfort inference, the predicted mean vote (PMV) model is not often applicable and data-driven methods using features from ambient environmental conditions have demonstrated moderate accuracies (60–75%). Therefore, the use of physiological sensing for improved performance has gained attention in recent years. Skin temperature has been widely used as an alternative indicator of human heat dissipation adjustment, which could be leveraged for personalized thermal comfort inference. However, considering the heat dissipation adjustments through skin as an adaptation mechanism in an environment, in this study, we have investigated the hypothesis that heat flux sensors could be an effective alternative for enabling feedback from human body to the control system. To this end, we designed and conducted an experimental study on 10 human subjects, wearing a thin-film heat flux sensor on their wrist, under transient thermal conditions (from 20 to 30ºC) to investigate the association between human thermal perception and the corresponding heat flux. Through this experiment, the correlations between heat flux, air temperature, relative humidity, and thermal preferences were analyzed. The high correlation factors (0.90 on average) between heat flux and thermal preferences suggest that heat flux sensors have a high potential to be used as an effective sensing modality in the HITL HVAC operation.

INTRODUCTION

The need for providing comfortable indoor conditions accounts for almost half of the energy consumption in buildings (U.S. Energy Information Administration, 2012; 2013). However, the current heating, ventilation, and air conditioning (HVAC) systems use inefficient operational strategies that often cause thermal discomfort to occupants (Huizenga et al., 2006). Specifically, setpoint temperatures are assigned by facility managers without occupants' direct perspectives (Jazizadeh et al., 2013a) and occupants often face difficulties in using thermostats (e.g., unknown locations and not user-friendly interfaces) (Karjalainen & Koistinen, 2007). Therefore, in the last decade, research efforts have attempted to address this missing link in the human-building interaction by leveraging the emerging information and communication technologies.

Among these efforts, occupant voting systems (OVS) has been proposed to facilitate occupant feedback data collection (Jazizadeh et al., 2011). This approach commonly relies on acquiring ambient condition data while occupants provide their feedback through smart mobile devices, which has led to personalized comfort profiling and inference. Kim et al. (2018) demonstrated that personalized comfort models outperformed the conventional comfort models (i.e., the predicted mean vote (Fanger, 1970) and adaptive model (De Dear et al., 1997)) when it comes to predicting occupants' thermal preferences (cooler, no change, and warmer). However, the personalized comfort predictive models showed median accuracies around 60 – 70% when they relied on environmental parameters (i.e., ambient conditions such as temperature, humidity, CO_2, etc.) (Ghahramani et al., 2015; Kim et al., 2018; Li et al., 2017b). This observation has led the research efforts to alternative techniques for personalized comfort quantification such as the use of physiological sensing systems (PSSs).

The human physiological processes autonomously respond to ambient environments as a property of homeostasis to maintain the core internal temperature to 37ºC (ASHRAE, 2017). One of the representative responses is the variations in blood flow to the skin by regulating blood vessels on the surface of the skin (expansion: vasodilation vs. constriction: vasoconstriction), which affects the skin temperature. Hence, skin temperature has been used as an indicator of heat dissipation adjustment of the human body (Jung & Jazizadeh, 2018b).

Given that the blood flow regulation on the skin is used to adjust the heat exchange rate with the surrounding environment, in this study, we have hypothesized that heat-flux sensors could be an effective sensing approach to reflect occupant thermal perception under transient thermal conditions. Understanding the thermal dynamics of occupants under transient thermal conditions calls for methods that are applicable, sensitive, and non-intrusive. By using a heat flux sensor, the heat exchange rate – the actual amount of heat dissipation from the body – between the human body and the environment can be measured. Previously, Shenoy & Diller (2018) conducted an experimental study with a heat flux sensor to check the heat transfer of a proxy of a human forearm (a polyvinyl chloride (PVC) cylinder) and showed positive feasibility in heat transfer measurement. In this study, we have employed the heat flux sensor with human subjects to investigate the feasibility of using heat flux as an effective feature for human-in-the-loop (HITL) HVAC system operations under dynamic thermal conditions. In doing so, we conducted an experimental study using a heat flux sensor, located on the wrist– in consideration of the position of wearable devices (e.g., smartwatches).

PREVIOUS STUDIES

As noted, OVS-based methods have played a key role in realization of personalized HVAC system operation, specifically in office buildings. According to the survey by Karjalainen & Koistinen (2007), thermostats – the interfaces for occupants' thermal feedback – are inaccessibly located in office buildings and office occupants are reluctant to control thermostats, even if they are accessible to them, due to the concern of authority. However, OVS-based techniques showed potentials for bridging the interaction gap between occupants and HVAC systems. Consequently, the previous studies have demonstrated that HVAC systems' performance can be improved by reflecting occupants' thermal feedback (Erickson & Cerpa, 2012; Jazizadeh et al., 2014; Murakami et al., 2007).

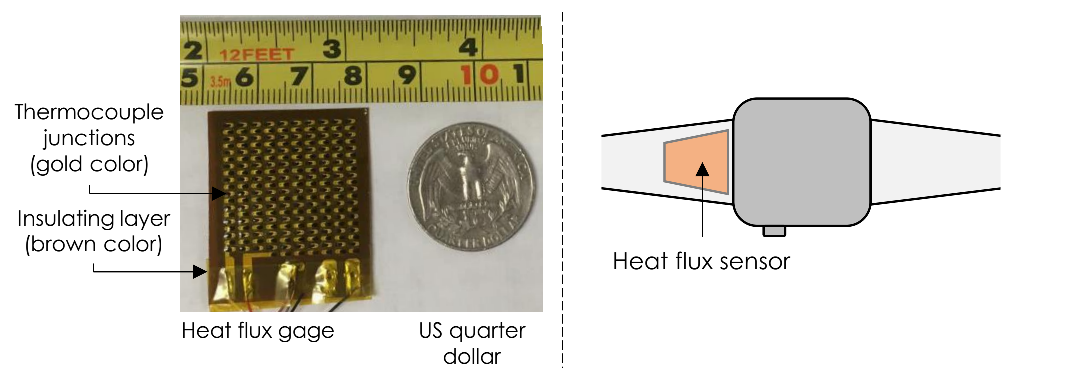
However, as noted, PSS-based methods have gained attentions for better personalized comfort inference. Ranjan & Scott (2016) employed the infrared imaging technique to measure participants' facial and hand skin temperatures and had 94 – 96% of accuracy in a two-class classification problem – whether energy use is required for occupants' comfort. Li et al. (2017a) also extracted human subjects' skin temperatures using smartwatches (a temperature sensor was embedded), coupled with a Random forest classifier, to classify subjects' thermal preferences, and showed an medium of 79% of accuracy. With the aim of expanding promising tools for PSS, we have introduced respiration quantification approaches by Doppler radar sensing systems (Jung & Jazizadeh, 2017a; Jung & Jazizadeh, 2017b; Jung & Jazizadeh, 2018a), and blood perfusion quantification approaches using RGB images (i.e., photoplethysmography-based signal analysis) (Jazizadeh & Jung, 2018; Jazizadeh & Pradeep, 2016; Jung & Jazizadeh, 2018b).

To enable human-centered control strategies, we have identified four core attributes for the human physiological sensing system (PSS): 1) applicability, 2) sensitivity, 3) non-intrusiveness, and 4) ubiquity (Jung & Jazizadeh, 2017b; 2018b). In other words, a reliable PSS method should be able to detect subtle variations in human thermophysiological data in the range of thermal variations in buildings while requiring minimal efforts from users. This study, another effort of exploring a novel PSS, aimed to demonstrate the potential of using heat flux sensors as an effective modality for PSSs.

METHODOLOGY

In this section, we introduced the heat flux sensor that we used in this study and the experimental study which we conducted to investigate the aforementioned hypothesis.

Heat flux sensor: Heat flux sensors generate electrical signals in proportion to heat exchange rate on the sensor surface (i.e., transducer; units are W/m^2). Specifically, we utilized a heat flux gage, manufactured by FluxTeq (FluxTeq, 2018) and specified in ASTM E2684-17 (2017), as shown in Figure 1 (a). This device consists of a differential thermopile made through holes in a sheet of polyimide (Kapton). It is about 150 µm thick with a corresponding time response of 0.6 sec. A large number of thermocouple junction pairs across the heat flux sensor generate a voltage difference that is proportional to the heat flux through the sensor. This provides a good signal with a reduced temperature disruption to the surface (Kreith, 2005).



(a) FluxTeq heat flux sensor and its dimensions

(b) Potential placement of the sensor In smart wearable devices

Figure 1. Heat flux gage used in this study

The advantage of this sensing technology lies at its flexibility and its design that could be adopted for different use cases. The inspiration of this study has come from not only the possibility of measuring heat exchange rate from the skin, but also the potentials of integrating it with wearable devices such as smartwatches. For example, if a part of the watch strap is composed of a heat flux sensor (Figure 1 (b)), occupants' heat exchange rate can be continuously measured in an environment, in which they interact with. For the data acquisition, we used MATLAB with a 3Hz sampling frequency.

Feature extraction and correlation analysis: Heat flux data contains noise, which needs a post-processing step to increase signal-to-noise ratio (SNR). As shown in Figure 2, we used two steps for the feature extraction: (1) the Savitzky-Golay filtering and (2) averaging the data by using a 30-second window. The first step is applied to reduce noise and redundancy. One of the advantages of the Savitzky-Golay filtering method is that it preserves the shape and height of waveforms using the local least-squared polynomial approximations (Schafer, 2011). The second step is to extract the averaged heat fluxes, when the subjects changed the thermal preference votes. Using these heat flux data, we performed correlation coefficient analyses with ambient temperature and relative humidity to check their associations.

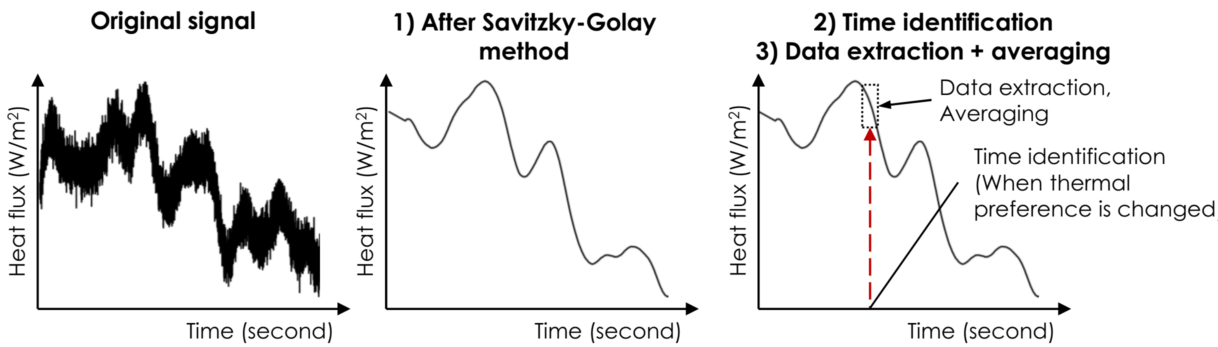


Figure 2. Post-processing for feature extraction (a schematic figure)

Experimental setup: We conducted an experimental study with 10 participants in a thermal chamber with dimensions of $4.2\times3.0\times2.8\text{m}^3$. The human subjects were students, whose ages were from 19 to 32 (7 male and 3 female students). We employed a transient thermal condition, with the objective of evaluating the applicability and sensitivity of heat flux sensors in providing near real-time feedback to HVAC systems. Hence, the experimental procedure was as follows: (1) human subjects waited outside the thermal chamber, which had a temperature of around 23ºC, for 10 minutes to ensure a stable thermoregulation state (e.g., eliminating the heat exchange effect from walking to the testbed), (2) they entered the testbed which was set at around 20ºC, sat on a chair, and attached the heat flux sensor on their right wrist, (3) the ambient temperature was increased at a pace of 1ºC per five minutes, (4) the subjects reported their thermal preferences using the values from +5 (warmer), 0 (no change), to –5 (cooler), and (5) the data was collected including heat flux, ambient temperature, relative humidity, and the subjects' thermal preference votes. The thermal preference voting scale, used in this study, is often utilized in recent studies instead of thermal sensation voting scale (e.g., hot, warm, neutral, cool, and cold) because of its direct indication of comfortable versus uncomfortable states.

DATA ANALYSIS AND RESULTS

To analyze the collected data, we empirically investigated the parameters for the Savitzky-Golay filtering and one polynomial order and a window size of 3,001 was assigned, which showed stable results on our data set. Figure 3 shows the variations of different parameters for one of the human subjects that manifested a representative trend in our dataset. At the beginning of the experiment (i.e., at the low temperature values), a higher heat flux was observed, indicating a higher heat dissipation rate for lower temperatures. In similar circumstances, seven out of ten subjects reported that they preferred a warmer condition - with thermal preference ratings varying between one and five (the heat flux range was from 106.7 to 301.6 W/m^2). As the temperature increased, we could observe a decreasing trend in the heat flux values. In high temperature conditions (around 27 – 30ºC), nine out of ten subjects expressed their preference of cooler conditions – with thermal preference ratings varying between –1 and –5 (the heat flux range was from 72.4 to 185.5 W/m^2).

This observation demonstrates that the human body perceives comfort in a certain range of heat exchange rate. In other words, if the heat exchange rate is out of this range, thermal discomfort is perceived. It is worth noting that individuals manifested different temperature and heat flux ranges for their comfort zones as shown in Table 1. The measurements show that the relative humidity decreased throughout the experiment, which was not intentionally planned for this experiment. This could be related to the fact that the testbed was a closed space (i.e., minimal infiltration was allowed). We do not consider the relative humidity as a major driver of thermal discomfort. This is based on our observation in a prior study with a longer period of measurements (Jazizadeh et al., 2013b). In this experimental study, only one participant (subject #1) expressed his discomfort regarding humidity at the end of the experiment (describing the room as too dry).

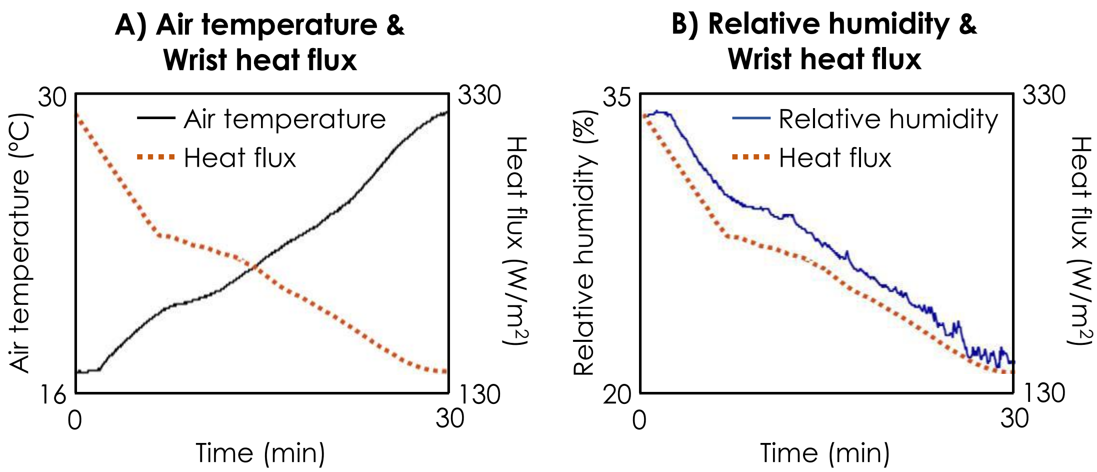


Figure 3. Wrist heat flux of Subject #1 and the experienced ambient condition

Table 1. Average air temperature and heat flux when each subject felt comfortable (i.e., no change in thermal preference was requested)

Subject	Air temperature (ºC)	Heat flux (W/m^2)
1	22.74	199.92
2	22.71	170.22
3	21.95	143.53
4	19.29	141.26
5	20.23	123.93
6	23.70	177.04
7	25.58	129.23
8	21.66	171.27
9	20.81	158.85
10	22.34	150.28

The feature extraction allowed for correlation coefficient analyses between the observed heat flux variations and ambient conditions at the times when each subject changed their thermal preferences (Table 2). As shown in Figure 3, heat flux had high negative correlations with ambient temperature (–0.963) and high positive correlations with relative humidity (0.959) and thermal preference in general (>0.879). We have noticed an outlier, specifically the correlation coefficient between thermal preference and heat flux for subject #8 (–0.803). Subject #8 reported no-change and warmer as thermal preferences throughout the experiment, and even preferred warmer at the peak ambient temperature, resulting in a negative correlation between heat flux and thermal preferences. We have presented the average correlation coefficients with and without the outliers (the values in the parentheses in the last row reflect the exclusion of the outlier). Exclusion of the outliers resulted in a higher correlation coefficient between thermal preference and heat flux.

Table 2. Correlation coefficients between heat flux and (i) relative humidity, (ii) ambient temperature, and (iii) thermal preference

Subject	Relative humidity vs. Heat flux	Ambient temperature vs. Heat flux	Thermal preference vs. Heat flux
1	0.995	–0.968	0.944
2	0.962	–0.990	0.971
3	0.972	–0.927	0.800
4	0.967	–0.955	0.911
5	0.993	–0.999	0.993
6	0.924	–0.970	0.655
7	0.976	–0.972	0.735
8	0.959	–0.962	–0.803
9	0.894	–0.929	0.973
10	0.964	–0.950	0.928
Average (average without outliers)	0.959 (0.959)	–0.963 (–0.963)	0.711 (0.879)

CONCLUSION

This study aims to demonstrate the potential of using heat flux sensors as an alternative physiological sensing system for human-in-the-loop (HITL) HVAC system operation, which has potentials for improved energy efficiency and occupants' comfort. Heat exchange rate between the human body and ambient environment triggers the human thermoregulation mechanism and might result in discomfort when it is out of a certain range. Hence, we hypothesized that heat flux sensors, which directly quantify heat exchange rates, could be used as an effective wearable sensing modality for HITL HVAC systems. Through an experimental study on 10 human subjects experiencing a transient temperature (from low to high), we investigated the applicability/sensitivity of heat flux sensors. Through this study, we acquired high correlation coefficients between ambient temperature/thermal preferences and heat flux values from the subjects' wrists (Table 2). Hence, heat flux sensors have a high potential to be adopted as an effective sensing modality for feedback to the building energy management systems. However, our observations showed that the heat flux sensor requires a consistent contact during measurements, otherwise it shows outliers and requires some time to be stabilized (i.e., obtain a similar datapoint when it is re-contacted with the skin). This constraint could be addressed by integrating heat flux sensors on smartwatches or other types of wearable devices, as depicted in Figure 1 (b). Considering the thin-film type of heat flux sensor that we used in this study, this can be a feasible solution as there was no human subjects, who complained about the attachment of the heat flux sensor to their wrists. For the future work, we aim to compare heat flux with skin temperature – the most commonly used physiological feature – by developing machine-learning algorithms, which use each parameter as inputs to predict occupants' thermal comfort. This will further demonstrate potential of heat flux sensors for HITL operation of HVAC system.

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