Dataset: Inferring Thermal Comfort using Body Shape Information Utilizing Depth Sensors

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ABSTRACT

Thermal comfort is very important for well-being and productivity of building occupants. It has been shown that body shape is a useful feature to determine thermal comfort of individuals [2]. It is because, the heat dissipation rate of individuals depends on the body surface area. As a result, a tall and skinny person can tolerate higher room temperature than a rounded body shape person [5]. In order to test this hypothesis, we performed a year-long experiment in 2017, where we recruited 77 participants and put each of them in a thermally controlled conference room in CMU for 3 hours and recorded their subjective responses regarding thermal comfort at different temperature ranging from 60°F to 80°F. In addition, we collected depth data of individuals using a vertically mounted Microsoft Kinect for XBOX One at the entrance of the conference room to capture their body shape. We also collected biometric features (e.g., Galvanic Skin Response (GSR), skin temperature) using a Microsoft Health Band worn by the subjects. The resulting dataset provides rich information regarding how different features can be used to infer thermal comfort of the individuals.

CCS CONCEPTS

• **Computer systems organization** → *Embedded and cyber-physical systems*; • **Human-centered computing**; • **Hardware** → *Sensor applications and deployments*;

KEYWORDS

Datasets, Thermal Comfort, Biometrics, Depth Data, Body Shape Estimation

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1 INTRODUCTION

Thermal comfort is crucial for physical and mental well-being as well as productivity of building occupants. However, it is very difficult to infer the thermal comfort preference of individuals as it is determined by many factors including air temperature, mean radiant temperature, air velocity, humidity, clothing insulation, and metabolic rate of individuals. Recent work [2] shows that body shape is a useful feature to determine thermal comfort of individuals. The reason is, the heat dissipation rate of individuals depends on the body surface area. As a result, a tall and skinny person can tolerate higher room temperature than a rounded body shape person [5]. As depth sensors are getting cheaper, they provide a viable opportunity to capture body shape information.

We perform data collection in a conference room in CMU. A Kinect for XBOX One was mounted at the ceiling of the entrance way of the conference room similar to [4] [3] as shown in Figure 1. We recruited 77 participants and put each of them in the conference room separately for 3 hours while we controlled the room temperature from 60°F to 80°F and received their subjective responses regarding their thermal comfort using a smart phone app. Each subject wore a Microsoft Health Band during the procedure that allowed us to capture different biometric features, e.g., GSR, and skin temperature.

2 DATA

Our dataset consists of the following information:

(1) **Depth Data:** Each subject was asked to stand underneath the depth sensor for one minute facing inside and one minute facing outside of the conference room. Then each subject was asked to walk in 10 times and walk out 10 times through the doorway so that we can capture body shape in motion. The Kinect was connected to an Intel Next Unit of Computing (NUC), where we collected raw depth frames at around 30 FPS. The resolution of each depth frame is 512x424, where

Figure 1: Deployment of an Microsoft Kinect for depth data-collection highlighted by a blue square.

each pixel gives us the distance from the sensor to the nearest object in millimeters. A sample depth image and corresponding RGB image is shown in Figure 2 when someone was walking in the conference room. Note that the RGB image here is only for illustration purpose. The dataset contains only the depth images. We remove the RGB images to protect the privacy of the participants.

(2) **Height and Shoulder Circumference:** A measuring tape was used to measure height and shoulder circumference of each subject. It can serve as ground truth for inferring body shape parameters using depth frames.
(3) **Weight:** A scale was used to measure weight of each subject.
(4) **Thermal Comfort Response:** A smartphone app was used to get subjective response from each subject about the level of thermal comfort in every five minutes. The subjects could provide responses in a five point scale: uncomfortably cold (-2), slightly uncomfortably cold (-1), comfortable (0), slightly uncomfortably warm (1), and uncomfortably warm (2). A screenshot of the app is shown in Figure 3.
(5) **Clothing:** For top clothing, the following classes were reported using the smartphone app: sleeveless blouse, short-sleeve shirt, long-sleeve shirt, sweater, sleeveless dress, short-sleeve shirtdress (thin), long-sleeve shirtdress (thin), and long-sleeve shirtdress (thin). For bottom clothing, the classes were shorts, long pants (thin), long pants (thick), skirt (thin), and skirt (thick). For outer layer clothing, the classes were sleeveless vest (thin), sleeveless vest (thick), long-sleeve sweater/jacket (thin), long-sleeve sweater/jacket (thick), and coat/suit jacket (thick).
(6) **Activity:** The participants reported their activity during data collection using the smartphone app as the follwing classes: lunchtime activity, meeting, presenting, recreation, socializing, working, and other.
(7) **Biometric Features:** Each subject was wearing a Microsoft Health Band that reported once in every minute the following biometric features: Galvanic Skin Resistance (GSR), calories burned per minute, and skin temperature of the participant's wrist.
(8) **Room Temperature:** Indoor air temperature was measured by the local thermostat in every minute.
(9) **Outside Temperature:** The outside temperature was measured by a weather station on campus in ten minute intervals.

(a) (b)

Figure 2: A sample depth image (a) and corresponding RGB image (b) of when someone is going in.

(10) **Outside Humidity:** The outside relative humidity (RH) was measured by a weather station on campus every ten minutes.
(11) **Gender:** Participants were asked to enter their gender before the start of the experiment.

Thermal comfort response, clothing response, activity levels, biometric features, room temperature, outside temperature, and humidity information are time synchronized and put together into a single CSV file for ease of analysis. An example of how to use this dataset to infer thermal comfort is available in [2]. The dataset is available for download from here [1].

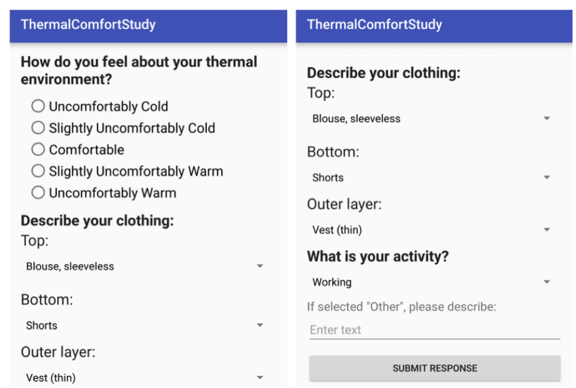

Figure 3: User interface of the mobile application that was used during the thermal comfort experiment.

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