

Data-Driven Approach to Control Air Temperature Based on Facial Skin Temperature

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ABSTRACT

Thermal comfort is a significant factor in the indoor building environment because it influences both human productivity and health. A currently popular method for predicting thermal comfort levels, the Predicted Mean Vote (PMV) and Predicted Percent Dissatisfied (PPD) model, unfortunately, has certain limitations. Consequently, the development of a better method for making accurate predictions (especially for individuals) is needed. Our goal was to develop a tool to predict individual thermal comfort preferences and automatically control the heating, ventilation, and air conditioning (HVAC) systems. This study adopted a series of human-subject experiments to collect essential data.

All collected data was analyzed by adopting different machine learning algorithms. The machine learning algorithms predicted individual thermal comfort levels and thermal sensations, based on facial skin temperatures of participants in the experiments. These predictions were input data for the HVAC system control model, and results supported the potential for using facial skin temperatures to predict thermal comfort and thermal sensation levels. Moreover, this tool provided automatic control of the HVAC systems that can help improve the indoor environment of a building.

INTRODUCTION

Although thermal comfort is a significant factor in an indoor building environment, the topic has not received sufficient attention because energy savings have previously been considered more important (Kubba 2012). Recent developments in architecture and systems design have made the reduction of energy consumption possible, and more attention has been directed toward the indoor environment. (Homod et al. 2012) The popular method for thermal comfort control is the PMV-PPD model, but that model has obvious limitations in making thermal comfort predictions (De Dear et al. 2013). First, it does not consider the changes in indoor environment that follow any change in the outdoor environment, but simply regards the indoor environment as stable. Another limitation of the PMV-PPD model is that it only includes the environmental parameters except clothing and metabolic rate (ASHRAE 2010). By ignoring personal parameters, such as body mass index, gender, age, and regional differences, the predictions are not as accurate. An accurate prediction for individual thermal comfort is necessary for improving the indoor environment and the productivity of its occupants. Our goal was to develop a prediction model for individual thermal comfort that could contribute to improvement of the indoor environment. The main prediction parameter was facial skin temperature, and the first objective was to investigate the relationship between facial skin temperature and thermal comfort. Moreover, an exploration of the influence of air temperature

on thermal comfort was necessary in order to promote adjustment to a building's indoor environment. Thus, the objective of this research was to develop a machine learning model that could be authenticated as a viable prediction process.

METHODS

There were four stages in this research: data collection experiments, data analysis, prediction model validation, and prediction model application. The experiments were conducted in an environmental chamber located in the basement of Watt Hall at the University of Southern California. (Fig.1) The experiment thermal environment was controlled by an independent heating and cooling system. Data collection was divided into two parts. The first one is for environment data collection, the second one is for human parameters collection. Sensors were used to collect facial skin temperature, air temperature, heart rate, and carbon dioxide level data. Meanwhile, the thermal comfort and thermal sensation levels were collected by survey.

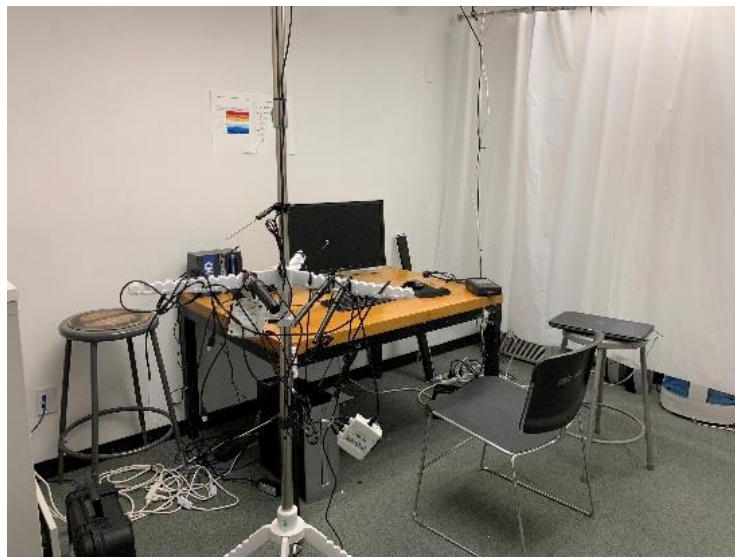


Figure 1. Environment chamber

The subjects in the experiments were volunteers recruited at the University of Southern California through the website. The plan was to test 20 subjects. In the early stage of the research, 5 subjects' experiment finished in the environment chamber. All of them are graduate students and the age range was narrow. The average age is 24. And there were 3 females and 2 males. They were required to wear long pants and short shirts to maintain the same clothing insulation rate. The experiment, that was divided into six temperature settings (Fig.2), lasted for 2 hours. To improve the accuracy of the experiments, the first 15 minutes were "adaption time" for the subjects. During that period, the subjects completed the first part of a survey, while wearing devices (Fig.3). The adaption time was meaningful to the subjects as it helped acquaint them with the experiment environment and become familiar with the experimental process. The first thermal comfort survey was given following the adaption time, and at the end of each temperature setting (each lasted for 15 minutes). The temperature changes in the experiment ranged from 20 °C to 32 °C. The temperature changing steps ranged from 2 °C to 4 °C. Moreover, temperature changes were randomly controlled, rather than having sequential changes, in order to identify the relation between facial skin temperature and the thermal comfort level in a static rather than a dynamic condition.

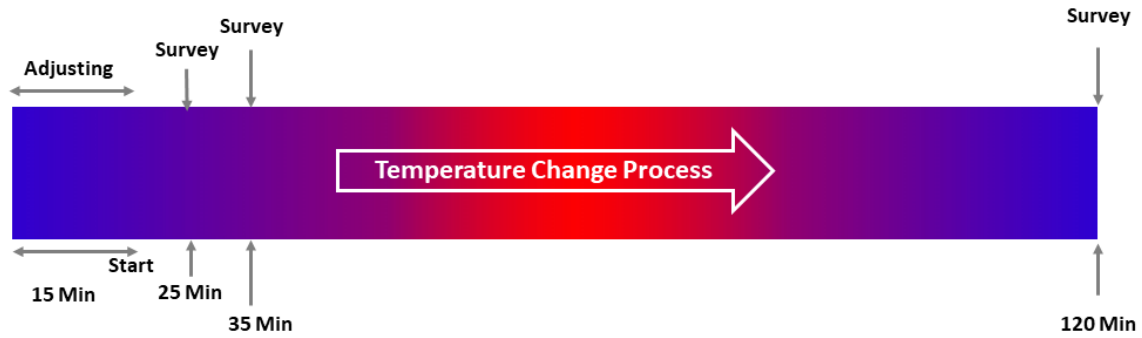


Figure 2. Experimental process



Figure 3. A subject in the experiment

Machine learning technology is a tool to achieve the automatic control of HVAC systems. The basic logic of the thermal comfort prediction is a classification model based on the data characteristics and tasks of the model. There were four classification algorithms chosen for this research: decision tree, logistic regression, random forest, and gradient boosting. The data collection software was Labview and the data analysis software was Python.

RESULTS

The data was collected every 5 seconds in the experiment. Nearly 1,000 data sets were collected for each subject during the experiment, and during the pre-processing step, data sets collected during an unstable indoor air temperature period were eliminated. The data for subject A were taken as an example of the data analysis process. Different facial points had different skin temperatures (Fig.4), with the forehead having the highest temperature and the cheek having the lowest temperature.

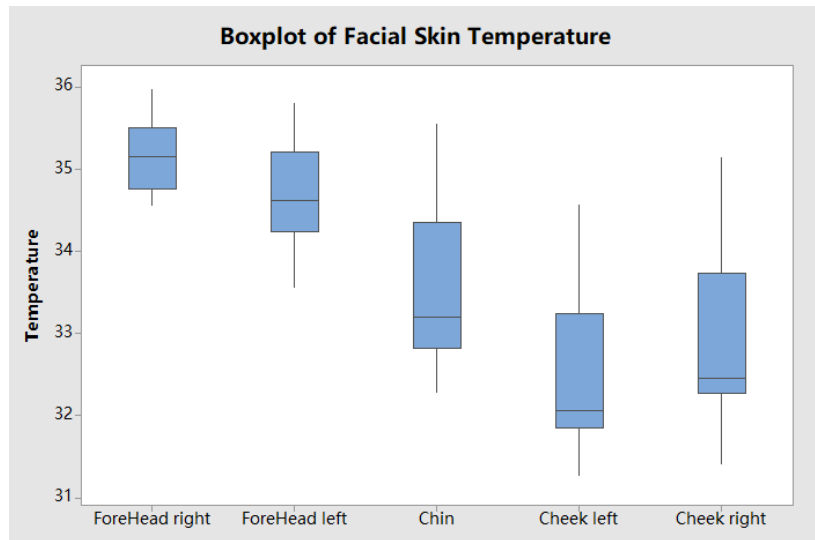


Figure 4. Facial skin temperature range

Air temperature was an important factor in thermal comfort evaluation (Metzmacher et al. 2018). The facial skin temperature had almost the same changing pattern as the air temperature which was measured at 1.1 meters. (Fig.5)

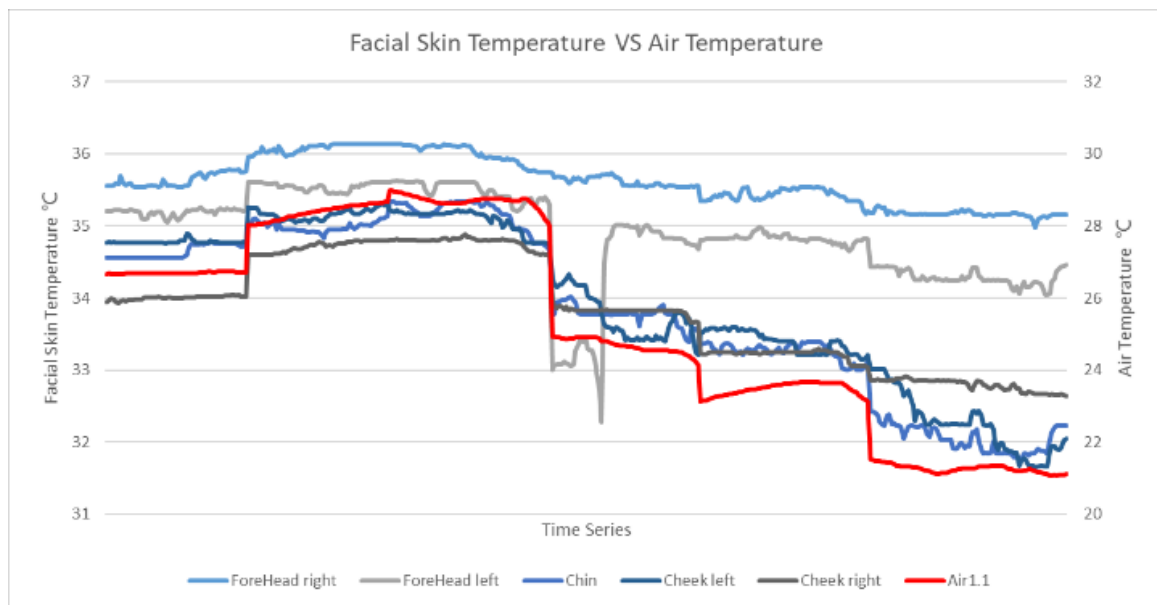


Figure 5. Facial Skin Temperature and Air Temperature Changing Patterns

The data analysis platform was Python. The basic prediction step divided the data set into two parts, with 75% of the data being used for training the machine learning algorithm and 25% of the data being used for testing the performance of the algorithm. The first step defined the importance of different facial parts in the thermal comfort and thermal sensation prediction. (Fig.6) The algorithm was Gradient Boosting. Feature importance represented the impact of different facial parts on the accuracy of predictions. Cheek right is the most important facial point for both thermal comfort and thermal sensation predictions.

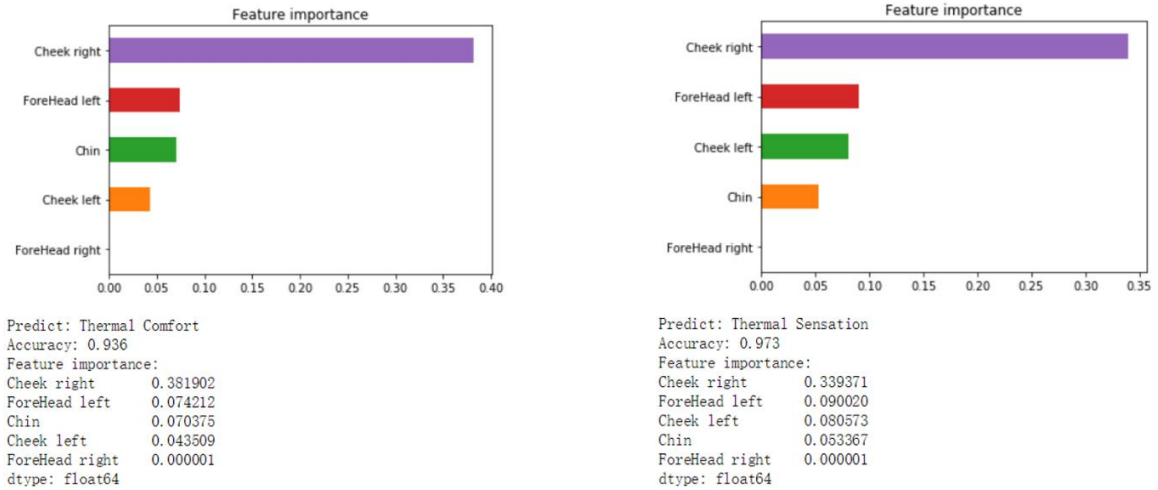


Figure 6. Feature importance of thermal comfort and thermal sensation prediction

To obtain a better analysis of the evaluations of thermal conditions, Decision Tree, Logistic Regression, Random Forest, and Gradient Boosting were compared in the analysis process (Fig.7). The input features were facial skin temperature, right cheek, left cheek, right side of forehead, left side of forehead, and chin. The output features were thermal comfort and thermal sensations. The output features were divided into three classes. For the thermal comfort prediction, the outputs were -1 (uncomfortable), 0 (neutral), 1 (comfortable). The outputs of the thermal sensation predictions were -1 (cold), 0 (neutral), 1 (comfortable). All algorithms had good prediction accuracy for the thermal sensation. For the thermal comfort prediction, the Logistic Regression did not perform well with an accuracy of only 78.1%. Others had good prediction accuracy up to 90%. The Random Forest classification model had the best performance for both predictions.

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Predicting Thermal Sensation
Using model: decision tree
Accuracy: 0.9678217821782178 +/- 0.05573430816434507
Using model: Logistic Regression
Accuracy: 0.9466019417475728 +/- 0.09248814991872646
Using model: Random Forest
Accuracy: 0.9752475247524752 +/- 0.04287254474180388
Using model: Gradient Boosting
Accuracy: 0.9727965443603184 +/- 0.04165022622157202

Predicting Thermal Comfort
Using model: decision tree
Accuracy: 0.9212531547272373 +/- 0.08133408522264605
Using model: Logistic Regression
Accuracy: 0.7807707241312366 +/- 0.1581724703148113
Using model: Random Forest
Accuracy: 0.9705882352941176 +/- 0.05094267081084935
Using model: Gradient Boosting
Accuracy: 0.9260823141137643 +/- 0.07429533940627915
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Figure 7. Thermal comfort and thermal sensation prediction accuracy

The thermal perceptions varied from different people. Each subject had an independent prediction model, and the analyzed process was the same with subject A. The data of five subjects were summarized. (Fig.8 and Fig.9) Random Forest was the best algorithm for subject A and subject B, while Gradient Boosting was the best algorithm for subject C and subject D.

When the appropriate algorithm was chosen, the prediction accuracy for both thermal comfort and thermal sensation for each subject could be more than 90%.

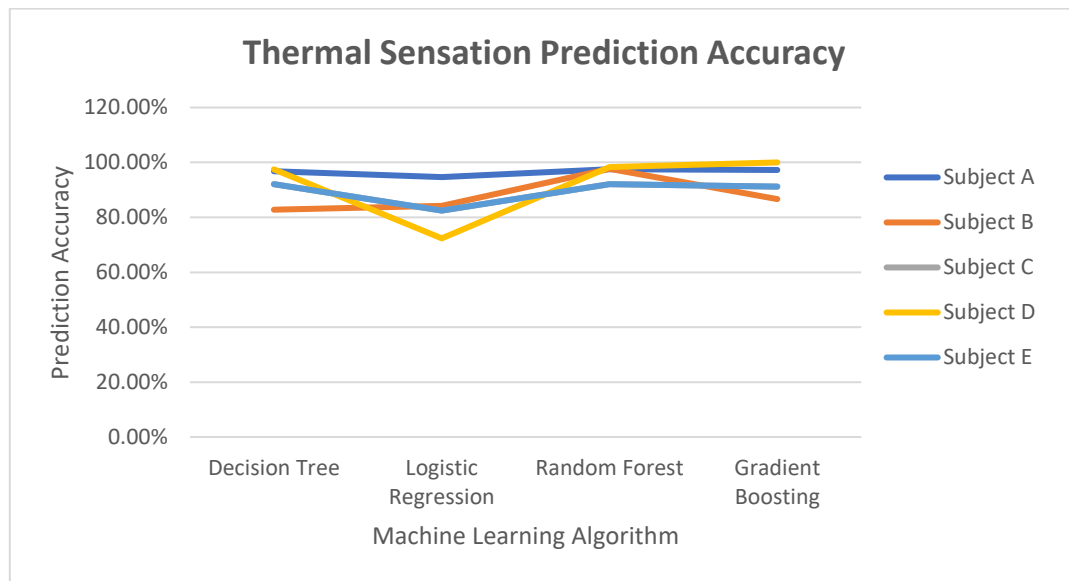


Figure 8 Thermal sensation prediction accuracy

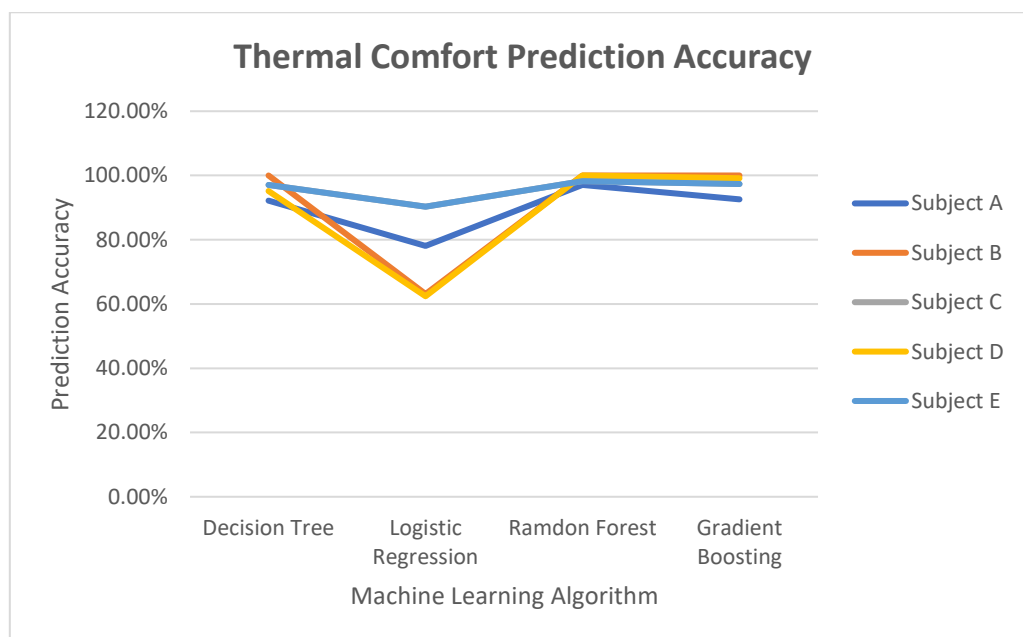


Figure 9. Thermal comfort prediction accuracy

DISCUSSION

The research used machine learning algorithm made predictions for thermal sensation and thermal comfort by using facial skin temperatures. Results showed various prediction accuracy and different suitable algorithms because the thermal condition preferences of individuals were different. The data-driven approach performed well on thermal condition predictions. It was necessary to select a suitable algorithm to help ensure accurate predictions. Individual facial parts played a variety of roles in the prediction process, illustrating the future potential for the application of prediction models. Moreover, the reasonable prediction accuracy obtained supports the possibility for automatic HVAC control systems based on facial skin temperatures.

CONCLUSION

The machine learning model is a good strategy for a HVAC control system. Facial skin temperatures can accurately portray thermal conditions, but thermal preferences vary for different individuals. Various facial parts have different skin temperatures even when the thermal conditions are the same. Based on results of our, the Random Forest and Gradient Boosting machine learning algorithms are suitable for predictions concerning thermal comfort and thermal sensations. The overall prediction accuracy ranged from 86.6% to 100%. However, there are limitations to this research. On the one hand, the accuracy for the surface sensor limited prediction accuracy and reliability. On the other hand, the data from validation experiments are necessary for the machine learning model.

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