Multimodal Sensing of Thermal Discomfort for Adaptive Energy Saving in Buildings

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Abstract

The paper describes our explorations in automatic human comfort prediction using physiological signals directly collected from a building inhabitants. Using a number of sensors, including a thermal camera and several bio-sensors (galvanic skin response, hear rate tracker, respiration rate tracker), we record a building's inhabitants under various thermal conditions (hot, cold, neutral), and consequently build a multimodal model that can automatically detect thermal discomfort.

The paper makes two important contributions. First, we introduce a novel dataset, consisting of sensorial measurements of human behavior under varied comfort/discomfort conditions. The change in physiological signals of the human body is monitored for several subjects, for different comfort levels in an indoor environment. Second, using the dataset obtained in the first step, we build a model that identifies the relationship between human factors and environmental conditions related to discomfort, with the final goal of automatically predicting the level of discomfort of a building inhabitant without any explicit input from the user. We measure the correlation between sensorial measurements collected from the user and self-reported levels of discomfort, and hence identify the sensorial measurements that are predictive of human discomfort.

This human-centered discomfort prediction model is expected to enable innovative adaptive control scenarios for a built environment in real time, as well as a significant reduction in building energy usage directly related to human occupancy and their desired comfort levels.

Keywords: thermal discomfort, multimodal sensors, PMV model, thermal imaging

1 Introduction

Recent statistics indicate that over 41% of the U.S. primary energy is consumed by the buildings sector [1], with resident buildings accounting for 54% of this energy consumption, and the remaining 46% for commercial buildings. Effective energy management in the buildings is one of the key factors impacting the overall energy consumption, and thus has important consequences on climate and the environment.

In the last few decades we have seen an increasing interest in the construction of energy-efficient buildings, which aim not only to optimize energy consumption but also to protect human health and provide comfort to their occupants. An important goal during the construction of energy-efficient buildings is controlling the thermal conditions in order to ensure a proper thermal comfort level for their occupants. Otherwise, occupants can seek other means to restore comfort, such as adjustment of air conditioners and fans or adding space heaters, which will further increase energy consumption. The reduction in energy consumption would have useful consequences on the climate and the environment. Human behavior studies have shown that individuals spent more than 90 % of their time indoors as compared to 10% of their time outdoors during the summer, and 4% during the winter [2]. Hence, energy consumption of buildings can be potentially reduced if thermal discomfort is detected early and comfort sensation is automatically restored.

This has motivated researchers to propose effective energy management strategies that can be used to design energy-efficient buildings and furthermore impact the overall energy consumption. Following this this line of research, this paper proposes a new methodology for detecting thermal discomfort, which can potentially reduce the building energy usage while improving the comfort of its inhabitants. In particular we focus on automatically detecting human discomfort by using physiological signals directly collected from buildings' inhabitants.

The paper makes two main contributions: a novel dataset consisting of sensorial measurements of the human body and a multimodal model to automatically detect discomfort. The data were collected using a thermal camera that records thermal videos of facial features, and several bio-sensors including galvanic skin response, heart rate tracker, and respiration rate tracker. The physiological measurements were collected from the occupants at different levels of comfort.

To identify the relationship between the measurements obtained (including the physiological signals and the environment conditions) with the thermal discomfort, we introduce a multimodal system that automatically predicts the level of discomfort of the building's occupants without any explicit action from the user. The system integrates the data collected from the multiple sensors and the thermal camera, and measures the relationship between these measurements and self-reported levels of discomfort obtained using the Predicted Mean Vote (PMV) model. An important application for this system is the automated restoration of thermal comfort for the building occupants that prevent them from seeking manual actions, which in turn can reduce the building's energy consumption.

2 Related Work

Thermal comfort can be defined from psychological, thermo-physiological, and heat-balance perspectives [3]. According to the psychological definition, thermal comfort is "That condition of mind which expresses satisfaction with the thermal environment" [4]. From the thermo-physiological perspective, thermal comfort is the minimum rate of nervous signals from the thermal receptors in the skin [5]. According to the heat-balance definition, thermal comfort is reached when the heat flow from and to the skin due to metabolism is balanced [6].

Measuring thermal comfort is challenging due to the subjective assessment and the psychological aspects [7, 8]. Additionally, the rate of metabolism differs from one individual to the other. The ASHRAE 55-2010 standard explains metabolic rate as the rate of transformation of chemical energy into thermal energy and mechanical work due to metabolic activities.

In general, there are six main factors that indicate thermal comfort. They can be divided into personal and environmental factors. Personal factors include metabolic rate and clothing insulation. In this paper, we limit the effect of personal factors by controlling the activity rate and clothing. The environmental factors include air temperature, mean radiant temperature, air velocity, and relative humidity. Air temperature is measured from the surrounding environments of the occupants. Mean radiant temperature expresses the effect of the temperature of the surrounding objects on the thermal comfort of the occupants [9]. Air velocity describes the rate of air movement across the occupant and has an important contribution to the (convective) heat transfer from the body. Relative humidity is the ratio between the actual water vapor present in the air to the maximum amount of water vapor needed for saturation at a given temperature.

Experiments have been conducted to analyze the thermal comfort of individuals considering both environmental and personal factors in indoor environments. Haldi and Robinson [10] applied probabilistic modeling using logistic regression to study the action of occupants sensing thermal discomfort in an indoor environment. Huizenga et al. [11] surveyed over 30,000 occupants in 215 buildings and concluded that high rates of thermal discomfort occurred in most buildings. Fang et al. [12] analyzed the effect of air temperature, humidity, and ventilation on the thermal comfort of office workers. Balaras et al. [13] investigated hospital operation rooms in order to achieve energy conservation without sacrificing the thermal comfort and the quality of services provided for patients. Ye et al. [14] investigated the thermal sensation of occupants in naturally ventilated buildings, where they applied the adaptive comfort model. Bessoudo [15] studied the impact of climate, glazing type, and shading properties on thermal comfort in an office environment in order to design energy-efficient buildings. Homod et al. [16] used PMV/PPD to detect thermal discomfort and combined a fuzzy model with a Gauss-Newton method for nonlinear regression algorithm in order to effectively control indoor thermal comfort. Hamdy et al. [17] studied the energy usage as well as the size of the cooling equipment required to achieve thermal comfort in an office building.

The effect of thermal comfort on individuals in an outdoor environment was evaluated for applications such as pedestrian comfort. Stathopoulos et al. [18] analyzed the integrated effect of air temperature, air velocity, relative humidity, and solar radiation on the human thermal comfort in an urban environment. Zhang and He [19] suggested strategies such as usage of solar shading in order to improve the thermal sensation of pedestrians in streets. Toudert and Mayer [20] conducted thermal experiments to show the effect of shading and surrounding surfaces on reducing thermal stress on individuals in an outdoor environment.

Multiple measurements are often taken to be able to accurately determine the main contributors to the sensation of discomfort. Ismail et al. [21] used thermal comfort multi-station to measure air temperature, air speed, relative humidity, illumination, and metabolism of students in a lab and determined that humidity and indoor air speed have the largest effect on sensing discomfort.

Physiological measurements can be also used to analyze the human body in order to determine how it is affected by thermal discomfort. It has been shown that temperature and skin conductance are important indicators of human thermal response [22]. Other measurements such as blood flow plays also a critical role in heat transfer between the body core and the skin. In hot weather, vasoconstriction occurs, which results in reduction of peripheral blood flow in the body. On the other hand, in cold weather, vasodilation occurs, which results in an increased peripheral blood flow. Accordingly, adapting thermally to hot weather is faster than cold weather [3]. Therefore, physiological measurements are fundamental to detect thermal discomfort.

Multimodal environmental sensors have been recently used to detect discomfort. Dang et al. [23, 24] constructed pedestrian navigation systems that choose passes to reduce thermal discomfort for pedestrians.

The research organized the massive data generated by the sensors using a multi-factor cost model and a data fuser in order to integrate multimodal data together in terms of thermal discomfort cost. Thermal imaging was used as a mean to detect discomfort of human owing to its advantage as a contact free method [25]. Based on a study on infrared thermography in humans [26], Oliveira et al. [27] used infrared thermal imaging to extract thermal regions of interest from the faces and applied fast Fourier transform to analyze these regions to assess thermal discomfort.

3 Experimental Discussion

3.1 Experimental Setup

Experiments were conducted in the living room area of the Zero Energy Laboratory shown in Figure 1, located at University of North Texas. Thirteen (13) graduate students from the Mechanical Engineering department participated in the experiments. The sample consisted of 3 female and 10 male participants with ages ranging between 22 and 35 years.

Figure 1: Zero Energy Building, where the experiments took place.

Physiological and environmental measurements in addition to thermal videos were collected for all participants. An overview of our system can be seen in the diagram shown in Figure 2. Physiological measurements were collected using four Thought Technology's FlexComp Infiniti sensors that were attached to the non-dominant hand of the participants. Two skin conductance electrodes were placed on the second and third fingers whereas the skin temperature and blood volume blood volume sensors were placed at the thumb and index fingers respectively. Measurements included: blood volume pressure (BVP), skin temperature (ST), respiration rate (R), and skin conductance (SC). The output of each sensor was obtained from a multimodal encoder connected to the main computer using an USB interface device. We recorded the combined output with the Biograph Infinity Physiology suite, which allowed us to visualize and control the data acquisition process. All measurements were taken at a rate of 2048/sec.

Environmental measurements were collected using HOBO Data Loggers sensors and included the building's air temperature and relative humidity. The wall temperature was also recorded using Newport True RMS super meter and the air speed inside the room was measured using an Omega HHF1000 sensor according to ASHRAE standard 55. The air and wall temperatures were recorded to make sure that they are in a fixed range of 73 °F to 76 °F during the experiments. Relative humidity was in the percentage range of

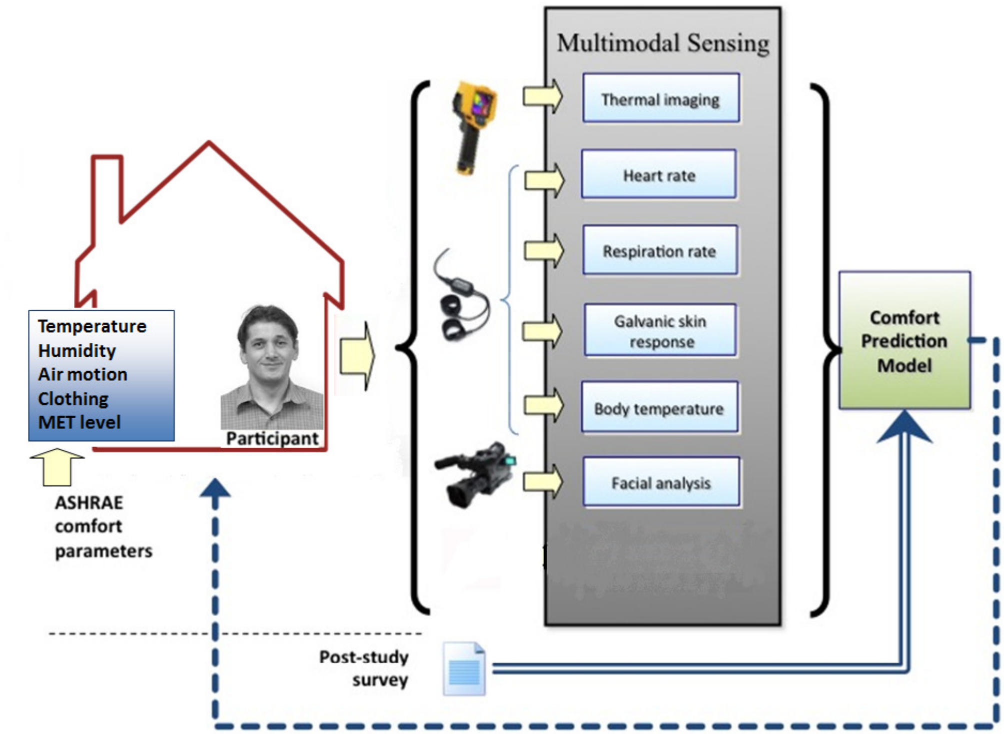

Figure 2: An overall view of our multimodal system, which includes the collection of physiological and environmental measurements in addition to thermal imaging of facial features and a thermal sensation survey.

lower to higher 50s. An electric fan was used in one stage of the experiments as explained below. The air speed was in the range of $0.8m/s$ to $3m/s$ for all the subjects. Additionally, clothing for all the subjects was limited to 0.57 Clo and the metabolic rate was controlled by specific metabolic activities. These settings were designed to eliminate external factors on the process of detecting discomfort.

The thermal videos were recorded using a Flir Thermovision A40 thermal camera. The features were extracted from the thermal videos using Flir's tools software and include the maximum, minimum, average, and max-min range temperatures of each frame at a rate of 60 frames per second. The max-min range refers to the temperature range between the maximum and minimum temperatures. Examples of thermal frames can be seen in Figure 3, where different ranges of colors indicate different temperatures (higher temperatures are shown as lighter colors).

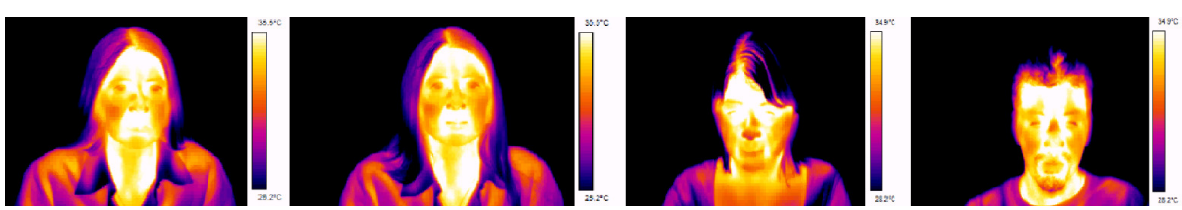

Figure 3: Examples of thermal frames.

3.2 Experimental Stages and Data Collection

The experiment was divided into three stages, which required a total time of 30 minutes for each subject (occupant). In the first stage, the individuals performed a 10 minutes workout on an air resistance elliptical machine inside the Zero Energy building. A metronome was provided to make sure that the exercise technique of all the human subjects was uniform, such that approximately 2.8 metabolic rate was performed by each subject during this activity. The activity was designed to produce an increase in the heat level of the human body and to observe its effect on thermal comfort level. After the activity, each occupant is asked to immediately sit on a chair where the four physiological measurements, in addition to the thermal videos, were recorded for five minutes. Note however that only the first recorded minute was used for our analysis.

In the second stage, the same measurements and recordings were collected for four additional minutes following the end of stage one. For this stage the last minute of the four minutes was used for data analysis. This stage simulates the adaptation of the human body to the surroundings and the relaxation back to a condition of no effort or activity.

In the third stage, an electric fan creates an air flow in front of each occupant for a period of 10 minutes. The physiological measurements and video recordings were collected for minute 10 of this period. This stage identifies the effect of air movement across the occupant's body without activity after relaxation and determines its effect on the thermal discomfort level. The continued airflow targets a constant cooling discomfort sensation by the occupants.

3.3 Comfort Level Survey

In order to evaluate the experienced comfort level we use the Predicted Mean Vote/Predicted Percentage of Dissatisfied or PMV/PPD model developed by Fanger [6, 28], which assumes steady state conditions in an indoor environment. The PMV rates thermal sensation of the subjects on a scale of (-3) for cold to (3) for hot. The surveyed individuals choose a value on the thermal scale to express their thermal sensation. PPD can be determined from PMV following that PPD increases when PMV shifts away in both directions from neutral, which is represented as (0) on the thermal scale.

We controlled the clothing and metabolic rate as described in section 3.1. Participants were surveyed one time for each of the three stages of the experiments on their thermal comfort sensation following the PMV scale. The scale ranged from (3) for hot in decrements of one down to (-3) for cold. Neutral is represented on the scale with (0). The first survey was taken right after the 10 minutes period of activity during the first stage. The second survey was conducted after the end of the four minutes taken to collect the measurements of the second stage. The third survey was conducted at the end of the third stage, after the fan operated for 10 minutes. The answers to the survey questions were collected in order to investigate the relationship between the reported levels of thermal comfort/discomfort and the physiological measurements, and thermal video recordings in order to automatically detect discomfort.

3.4 Method

In order to identify the relationship between physiological measurements and thermal responses (represented by the PMV scale) we opted for performing a correlation analysis. Pearson's correlation coefficients supported with the $P - value$ were calculated. The coefficients specify the strength of the relation between two measurements and whether this relation is directly or inversely proportional. We used this analysis to gain insight into the underlying relations between the studied physiological responses and the reported thermal comfort.

Our next step consisted of applying a machine learning approaches by using a decision tree classifier. The data set was divided into training and test sets. The thermal features synchronized with the physiological measurements were used as input to a learning system that creates decision trees learned from the training data. The system creates a model, which automatically classifies untrained test data as indicators of a state of thermal comfort/discomfort.

3.5 Experimental Results

3.5.1 Correlation Statistics

Each of the 13 occupants reported a single thermal score for each of the three stages. Therefore, we have a total of 39 collected scores. Using a total of eight physiological and thermal measurements, we measured the correlation statistics using three different ways. First, the collected measurements were averaged for each occupant during each stage to get a single averaged value for each of the eight measurements. The correlation coefficients were calculated to identify the relation between the averaged measurements and the thermal score reported by each occupant using the PMV model. The results showed that the correlation coefficients of the thermal score with BVP physiological measurement, maximum thermal temperature, and max-min range are 0.56, 0.56, and 0.33, respectively. These results were supported with a $P-value$ that is less than 0.0001. The correlation coefficients of all other measurements were not statistically significant. This indicates that the three measurements are directly proportional to the PMV thermal scale.

Second, the occupants were divided into two groups to present the three stages of experiments. For these results, the differences between each occupant's measurements for the three stages were considered. In particular, the first group includes the measurements of the first stage subtracted from those of the second stage in order to measure the difference in the occupant's collected measurements in the transition from heat discomfort to comfort. The second group includes the measurements of the second stage subtracted from those of the third stage to measure the difference in the collected measurements in the transition from comfort to cold discomfort. The differences in the thermal scale scores reported by the occupants were calculated accordingly. The correlation coefficients were measured as before, however, separately for each group. The coefficients are shown in Table1.

Table 1: Correlation coefficients of the differences in the thermal score in relation to the eight physiological and thermal measurements. Statistically significant results are in bold with $P < 0.0001$. (blood volume pressure (BVP), skin temperature (ST), respiration rate (R), skin conductance (SC))

Group	BVP	ST	R	SC	Max	Min	Avg.	Max-Min
First group	0.19	**0.31**	**0.43**	**0.35**	-0.16	0.13	**0.43**	-0.16
Second group	**0.33**	-0.08	-0.06	-0.10	**0.42**	0.08	-0.02	0.19

The results indicate a significant relationship between skin temperature, respiration rate, skin conductance, and average thermal temperature on one side and the differences in the thermal scale for the first group representing the transit from hot discomfort to neutral on the other side. Moreover, a significant relationship was observed between BVP and the maximum thermal temperature with the thermal scale for group two in the transit from comfort to cold discomfort. This indicates that specific measurements can indicate the state of transition from discomfort to comfort and vice versa.

Third, the collected measurements were divided into three groups based on the occupants' reported thermal scale score. Hence, one group represents the measurements of those who reported (0) as an indication of thermal comfort, the second group represents those who reported a score above (0) as an indication of hot discomfort, and the third group represents those who reported a score below (0) as an indication of cold discomfort.

Given that each occupant reported three scores for each stage of the experiments to form a total of 39 samples, the first, second, and third group consisted of measurements of 9, 16, and 14 samples, respectively. The physiological and thermal measurements were averaged for each second, which gives a total of 60 values for each of the eight measurements for each sample. The correlation coefficients were calculated to identify the relation between the eight measurements with each other for each group. This results in an 8×8 symmetric correlation matrix for each group. The idea is to identify the relation between specific measurements for each of the three states of comfort, hot discomfort, and cold discomfort. However, the correlation coefficients between the maximum and minimum thermal measurements with the average and max-min thermal range were ignored due to the dependency between them. Table 2 presents the statistically significant correlation coefficients between different measurements if they exist for at least one of the groups. In addition, the coefficients must be significantly different from one group to the other in order to be present in the table. Other statistically insignificant results were not reported. Note that some measurements are not reported in the table, as they did not exhibit a significant correlation with other measurements.

Table 2: Correlation coefficients between the eight measurements with each other for each group. Statistically significant results are reported. N/A indicates a correlation of a measurement with itself and (–) indicates a coefficient that is not statistically significant or not different from one group to the other.

Group	Measurement	R	SC	Max	Min	Avg.	Max-Min
Comfort	ST	-0.51	0.52	–	0.40	–	-0.58
	R	N/A	–	–	-0.54	-0.63	0.47
	SC	–	N/A	-0.38	–	–	–
Hot Discomfort	ST	-0.14	0.44	–	0.01	–	-0.09
	R	N/A	–	–	-0.20	-0.13	0.14
	SC	–	N/A	-0.01	–	–	–
Cold Discomfort	ST	0.13	0.29	–	-0.02	–	-0.31
	R	N/A	–	–	-0.36	-0.39	0.25
	SC	–	N/A	-0.04	–	–	–

It is interesting to observe that the state of comfort exhibited the highest correlation coefficients whether they were directly or inversely proportional. It can be noted that the significance of these relations were reduced with the state of both hot and cold discomfort. For instance, in the state of thermal comfort, the coefficient between the respiration rate (R) and the skin temperature (ST) was -0.51. This changed to -0.14 with hot discomfort and 0.12 with cold discomfort. Additionally, it can be noted that the measurements for cold discomfort are statistically more significant than those of hot discomfort and are closer to those of the comfort state. This indicates that the thermal and physiological measurements of the cold discomfort and comfort states are more related compared to hot discomfort. The correlation between these specific measurements can be used as indicators of the state of thermal comfort/discomfort.

3.5.2 Automatic Classification of Human Discomfort

To further investigate and analyze the collected measurements and their ability to automatically detect discomfort, a learning system was created using a decision tree classifier. Using a set of 39 reported thermal scores as samples, a dataset was created with three classes; comfort, hot discomfort, and cold discomfort. Given the low number of samples we had, a leave-one-out cross validation scheme was used for training and the average results were reported. Two approaches were followed to automatically detect discomfort. First, the thermal and physiological measurements were averaged per second to have a matrix size of 60×8 which is transformed into a feature vector for each sample. Second, all the measurements were averaged to get a single value for each measurement, i.e., a vector of size 1×8 to represent each sample. For both approaches, feature selection was used to determine which features/combination of features exhibited the highest discomfort prediction capability.

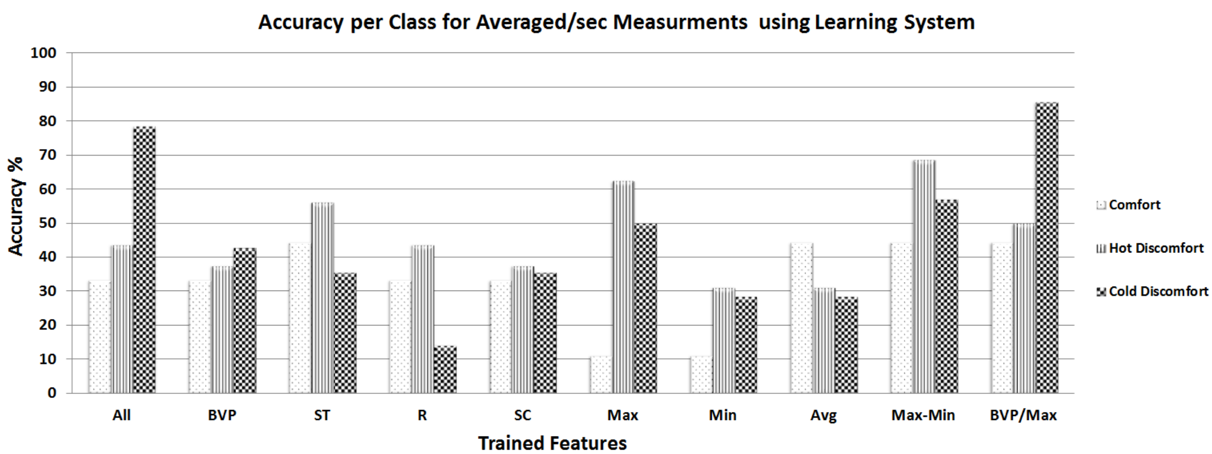

Figure 4: Per-class accuracy for the first approach using all features (baseline), individual features, and best feature combination, respectively.

Using the first approach, Figure 4 shows the accuracy per class using all features together, each feature individually, and the combination of features that achieved the highest average accuracy. On average, the performance using all features was 53.8%, which represents better performance than the individual features. However, the combination of BVP and the maximum thermal temperature achieved the highest overall accuracy of 61.5%. This agrees with the correlation statistics that indicated that these two measurements along with the max-min range are the best predictors of the state of thermal comfort/discomfort. Moreover, it can be noted that the hot discomfort class had the highest accuracy out of the three classes with six out of eight results for the individual features. However, the cold discomfort class achieved the highest accuracy with the BVP/Max feature combination.

Figure 5 shows that in general the second approach yields higher accuracies compared to the first approach. As observed earlier, none of the individual features achieved higher overall accuracy than that of the baseline of 64.1%. Moreover, five out of eight results of training individual features indicated a higher

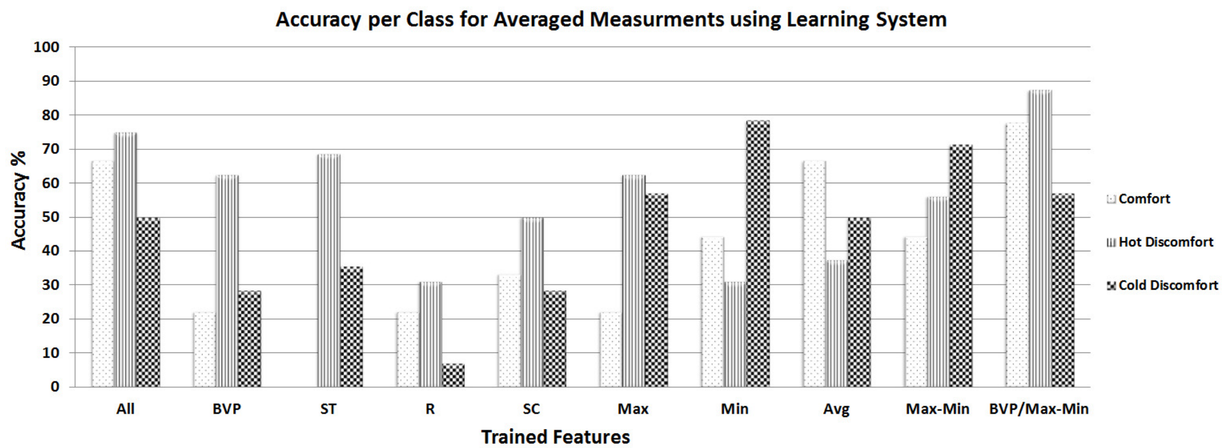

Figure 5: Per-class accuracy for the second approach using all features (baseline), individual features, and best feature combination, respectively.

capability of predicting hot discomfort. The other three features had higher prediction capability for cold discomfort. The combination of BVP with max-min range thermal measurement achieved the highest overall accuracy of 74.4%. This as well agrees with the correlation statistics observed earlier.

4 Conclusion

Designing energy-efficient building coupled with effective energy management are key factors impacting the overall energy consumption in U.S., and ultimately has important consequences on the global climate and the environment. To achieve that, the thermal discomfort of buildings' occupants needs to be well understood and if possible automatically detected. A model could then be built to identify the relationship between human factors and environmental conditions related to comfort, and to automatically predict the level of comfort of a building inhabitant without any explicit input from the user. This human-centered comfort prediction model can enable real time and more effective control of the environmental conditions, maximizing both human comfort and energy savings. In this paper, we presented our initial experiments in the process of automatically detecting thermal discomfort. Our research contributes a novel dataset and a multimodal system that detects discomfort. The dataset was collected from a number of occupants of a building using a total of eight physiological and thermal measurements. Moreover, the occupants reported a score of their thermal sensation following the PMV static model. Other environmental factors as well as metabolic rate and clothing were measured and controlled to fairly assess the thermal discomfort sensation.

Multiple correlation statistics and machine learning approaches were conducted to identify the relationship between the collected measurements and the state of comfort/discomfort reported by the occupants. Experimental results showed that the correlation statistics and learning approaches agreed on three measurements that had the highest capability of predicting thermal discomfort of occupants, namely blood volume pressure, maximum thermal temperature, and max-min thermal range. Additionally, it was concluded that specific measurements had statistically significant correlation with each other in the state of comfort. When the comfort sensation transform to hot or cold discomfort, these correlations are significantly reduced.

In the near future, we are planning to collect more data from a large number of occupants under multiple states of comfort/discomfort, which is likely to result in improvements in the accuracy of our multimodal discomfort prediction system. Additionally, more physiological and thermal measurements parameters will be collected to allow for further data analysis. The improvement expected with larger data can exert higher prediction capability of thermal discomfort and can contribute to reduced energy consumption and more effective design guidelines for energy-efficient buildings.

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