Detecting Human Thermal Discomfort via Physiological Signals

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ABSTRACT

This paper provides a new approach to the automatic detection of thermal discomfort. We see this research as a step toward the development of an intelligent climate control system that does not require any explicit input from the users. We introduce a novel dataset that simulates different thermal comfort/discomfort levels and we provide a complete analysis of different physiological signals and their capability of discriminating between these levels. Our approach is successful in detecting the thermal sensation of human subjects and it is expected to enable innovative adaptive control scenarios for enclosed environments as well as a significant reduction in energy consumption.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Miscellaneous

Keywords

thermal discomfort; physiological signals

1. INTRODUCTION

Different studies reported that the air conditioning inside vehicles consumes up to 30% of the fuel in conventional internal combustion engine vehicles, and can reduce the range of the vehicle's battery by up to 40% in electric cars [15]. Studies suggested that raising a vehicle's temperature by four degrees Celsius can save approximately 22% of the compressor power leading to a 13% increase in the coefficient of performance [14]. Accordingly, the first step in achieving the trade-off between thermal comfort and reduced energy consumption is the automated detection of the thermal sensation levels of individuals, in order to automatically adjust the temperatures using a climate control system and hence retain a thermal comfort sensation.

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Different personal and environmental factors control the thermal sensation of individuals. Personal factors include the metabolic rate and clothing insulation, while environmental factors include air temperature, mean radiant temperature, air velocity, and relative humidity. However, recent research showed a significant difference between human thermal sensation in buildings and in vehicles [13, 3]. In particular, other factors contribute to thermal discomfort in vehicles such as the effect of solar radiation and poor interior insulation.

With the massive developments in vehicle technologies, companies have started to develop seat belts that are capable of detecting certain physiological measurements such as the heart rate and respiration rate of the occupants, for purposes such as detecting a driver's drowsiness. Hence, these measurements can eventually play a crucial role in real-time detection of the individuals thermal discomfort levels.

This paper proposes an approach to automatically detect different levels of an individual's thermal comfort and discomfort, paving the way of developing a completely automated climate control system. In particular, this paper makes four main contributions. First, it introduces a novel dataset collected from 50 subjects including simulations of comfort, cold discomfort, and hot discomfort using self-reported levels of discomfort with the Predicted Mean Vote (PMV) model. In order to have full control of the thermal environmental conditions, an insulating enclosure was built that was connected to a heat pump/air conditioning unit. Second, we utilize four different physiological sensors to collect measurements from the subjects. Third, we provide an analysis of the specific type of physiological measurements that is most capable of indicating the thermal sensation of the subjects. Finally, we develop an approach that detects different levels of cold discomfort as well as different levels of hot discomfort separately.

2. RELATED WORK

Methods have been proposed to detect thermal discomfort in indoor environments. Freire et al.[5] developed two control algorithms using only-one-actuator system in order to achieve energy consumption minimization while maintaining the indoor thermal comfort. Homod et al. [8] combined a fuzzy model with a Gauss-Newton method for nonlinear regression algorithm in order to effectively control indoor thermal comfort using the PMV/PPD model. Hamdy et al. [7] analyzed the energy usage and the size of the cooling equipment needed to achieve thermal comfort in an office building. Haldi and Robinson [6] studied the action of occupants sensing thermal discomfort in an indoor environment using probabilistic modeling. Huizenga et al. [10] observed high rates of thermal discomfort occurring in buildings by surveying over 30,000 occupants in 215 buildings.

More recently, detecting thermal discomfort in vehicles gained more interest. Simion et al. [13] analyzed the personal and environmental factors that affect the discomfort sensation in vehicles. Studies showed that the discomfort sensation in vehicles differs from buildings as it includes other factors such as the effect of solar radiation, poor interior insulation, and the non-uniformity of the average radiant temperature [3]. Another study analyzed the vehicle thermal discomfort parameters in order to improve the detection methods and reported the inside temperature and relative air humidity as the main contributors to thermal sensation in vehicles [12].

Physiological signals were used to analyze the human body response to thermal discomfort. Karjalainen [11] analyzed the effect of temperature and skin conductance as indicators of human thermal response. Other measurements such as blood flow plays also a critical role in heat transfer between the body core and the skin. In hot weather, vasodilation occurs, which results in increasing the width of the blood vessels. On the other hand vasoconstriction occurs in cold weather resulting in narrowing the blood vessels in the body to decrease the blood flow and keep the heat. Hoppe [9] showed that adapting thermally to hot weather is faster than cold weather.

Multimodal sensing had been recently used to detect thermal discomfort. Dang et al. [4] developed a navigation system that chooses passes to reduce thermal discomfort for pedestrians. A preliminary study showed the potential of combining thermal imaging with certain body signals in improving discomfort detection rates [2].

3. DATASET

3.1 Subjects

Our dataset consists of recordings collected from 50 volunteering students and adults from the University of Michigan. The subjects included 32 males and 18 females, came from different ethnic backgrounds, and had an age range between 18 and 60.

3.2 Devices

We employed four bio-sensors to collect physiological responses, namely blood volume pulse (BVP sensor), skin conductance (SC sensor), skin temperature (ST sensor), and abdominal respiration (BR sensor). Two skin conductance electrodes were placed on the second and third fingers, whereas a skin temperature and blood volume pulse sensors were placed on the small and index fingers, respectively. The respiration sensor was placed comfortably around the thoracic region. A computer was used to collect the signals from the sensors through a multimodal encoder. The physiological measurements were collected using Biograph Infinity Physiology suite.[1] Thermal cameras were also used to capture videos for the subjects and will be processed in future work.

3.3 Experimental Procedure

In order to simulate a small enclosed environment similar to that in vehicles, we built an enclosure at the University of Michigan with insulating material for complete isolation from the room temperature. The enclosure was connected to a heat pump in order to blow hot and cold air. It also had a slit to allow the connection of the physiological sensors and the recording of the thermal cameras. A picture of this system can be seen in Figure 1.

[1]http://www.thoughttechnology.com/physsuite.htm

Figure 1: The experimental system including an insulating enclosure, physiological sensors, and thermal cameras.

The subjects were asked to sit comfortably on a chair in the enclosure and the four physiological sensors were connected. The data collection process encompassed three stages.

3.3.1 Comfort

The subjects were asked to stay in the building where the experiments were conducted for a period of time, to adapt to the indoor temperature and feel thermally comfortable. Then they were asked to sit in the enclosure and stay inside till the end of the experiments. The subjects were then recorded for four minutes in this state.

3.3.2 Cold Discomfort

In this stage, cold air was blown into the enclosure using the heat pump and a fan while the subjects were sitting inside. This process was continued for approximately 20 minutes until the enclosure temperature reached approximately 61F. The subjects were then recorded for four minutes with the cold air continuously blowing.

3.3.3 Hot Discomfort

In this stage, hot air was blown into the enclosure using both the heat pump and an electric heater while the subjects were sitting inside. This process continued for approximately 10 minutes until the enclosure temperature exceeded 95F. The subjects were again recorded for four minutes with continuous blow of hot air.

3.3.4 Thermal Sensation Rating

To evaluate the comfort/discomfort level of the subjects, the Predicted Mean Vote/Predicted Percentage of Dissatisfied or PMV/PPD model developed by Fanger [1] was used, which assumed 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.

At each of the three stages, the subjects were asked to rate their thermal sensation using the PMV scale. All the subjects rated the comfort stage as “0", which represents the thermally neutral state on the PMV scale. For cold discomfort, the subjects’ ratings ranged from -1 to -3. Similarly for the hot stage, their ratings ranged from 1 to 3.

4. EXPERIMENTAL DISCUSSION

4.1 Feature Extraction

Physiological measurements were collected by processing raw signals from each sensor. The Biograph Infiniti Physiology suite was used to obtain physiological assessments for heart rate from the blood volume pulse (BVP), skin conductance (SC), respiration rate (RR), and skin temperature (ST). These measurements were obtained at the highest sampling rate available, which is 2048 samples per second. The physiological feature set consisted of raw measurements and their statistical descriptors, including maximum and minimum values, means, power means, standard deviations, and mean amplitudes (epochs). In addition, we obtained features derived from inter-beat intervals (IBI) measurements such as the minimum and maximum amplitudes and their intervals. The final set formed a total of 59 physiological features including 40 BVP features, five SC features, seven RR features, five ST features, and 2 features extracted from the BVP and the RR sensors combined, namely, the mean and heart rate max-min difference, which is a measure of breath to heart rate variability.[2]

4.2 Classification

A decision tree classifier was used to detect the comfort state as well as different discomfort states of the subjects using a leave-one-subject-out validation scheme. In this scheme all the three instances of each subject were reserved for testing while all the other instances were used for training in order to avoid any bias. We report the overall accuracy as well as the recall of each class and compare them to the baseline performance of random guessing. We analyze whether the integration of features improves the performance as well as the capability of each sensor in specifying the thermal sensation of the subjects. We also use two different classification schemes. First, we categorize the instances into three classes, comfort, cold, and hot. Second, we categorize the data into seven classes based on the reported ratings of each subject using the PMV scale.

4.3 Experimental Results

Table 1: Overall accuracy as well as the recall of each of the comfort, cold discomfort, and hot discomfort classes for the raw data, individual physiological features, and all features combined.

	Baseline	4 Raw	BVP	SC	RR	ST	All
Accuracy	33.3	74.7	53.3	39.3	32.0	**76.0**	72.0
Comfort	33.3	60.0	52.0	44.0	36.0	68.0	**72.0**
Cold	33.3	**98.0**	60.0	40.0	38.0	90.0	86.0
Hot	33.3	66.0	48.0	34.0	22.0	**70.0**	58.0

Table 1 lists the overall accuracy and the recall of the comfort, cold discomfort, and hot discomfort classes as well as the baseline performance, for the raw data, individual physiological sensors features, and all features combined. The raw features consist of the four raw physiological measurements directly collected from the sensors. The individual physiological sensors features represent all the features extracted from each sensor separately as specified earlier. All features combined represent all the 59 physiological features. The -1, -2, and -3 ratings were combined into the cold class and the 1, 2, and 3 ratings were combined into the hot class.

The table shows that the skin temperature features achieve the best overall accuracy. The heart rate features achieve the second best performance among other sensors with a relative improvement of 60.1% over the baseline. The four raw features and all the features combined achieve a comparable accuracy as well to the skin temperature features. The features provided by the three other sensors did not perform as well especially the respiration rate features.

Interestingly, the best detected state is the cold discomfort reaching 98% using the four raw features. This state also achieves an improved performance with the skin temperature features and all the features combined. The comfort and hot discomfort classes exhibit close performance, which is less accurate than the cold discomfort class.

Table 2: Overall accuracy as well as the recall of each of the comfort, three cold discomfort, and three hot discomfort classes for the raw data, individual physiological features, and all features combined.

	No.	Baseline	4 Raw	BVP	SC	RR	ST	All
Accuracy		33.3	44.2	31.3	19.0	28.6	**47.6**	46.3
Comfort	49	33.3	**71.4**	49.0	49.0	44.9	67.3	59.2
Cold -1	17	11.6	17.6	**23.5**	0.0	11.8	**23.5**	**23.5**
Cold -2	20	13.6	25.0	20.0	0.0	20.0	**50.0**	45.0
Cold -3	12	8.2	**50.0**	33.3	8.3	0.0	16.7	25.0
Hot 1	14	9.5	28.6	14.3	0.0	0.0	7.1	**35.7**
Hot 2	29	19.7	41.4	27.6	10.3	48.3	**69.0**	62.1
Hot 3	6	4.1	0.0	0.0	0.0	0.0	0.0	0.0

Table 2 lists the overall accuracy and the recall of the comfort, the three cold discomfort, and the three hot discomfort classes for the raw data, individual physiological sensors features, and all features combined. The second column presents the number of instances belonging to the corresponding class. It should be noted that the specific cold and hot ratings for one of the subjects were missing due to an error in collection and hence the results of this table are for 49 subjects.

Similar to Table 1, the skin temperature sensor, the four raw features, and all features combined achieve the best performance. Overall, the majority of the results are above the baseline. On the other hand, the skin conductance and respiration rate sensors achieve poor performance in the majority of the cases.

In general the three cold classes exhibit improved performance to the three hot discomfort classes. Hot 2 class achieves better performance compared to the hot 1 and hot 3 classes. This could be attributed to the unavailability of enough training instances for the hot 3 class in particular.

Overall the table shows that our approach is capable of differentiating between different levels of cold and thermal discomfort. However, the system needs to be trained on additional instances for each class for better separability.

In order to analyze the best performing set of features, as obtained from the skin temperature sensor, as well as the reason for the improved performance of the cold discomfort class compared to the hot discomfort, Figure 2 shows the sorted average temperatures in F collected from the skin temperature sensor throughout each of three states of comfort, cold discomfort, and hot discomfort for each of the 50 subjects. The figure provides some interesting observations. First, the cold discomfort curve is well separated from the other curves. On the contrary, the hot discomfort and comfort curves are very close. Second, some temperatures could result in comfort sensation for certain individuals while resulting in hot sensation for others. This can also be seen for a few subjects at the higher end of the cold discomfort curve. Third, the human body needs a much longer time to go from the comfort stage to the cold discomfort state and needs approximately half that time to transfer

[2]This set of 59 features includes the four raw features collected directly from the sensors.

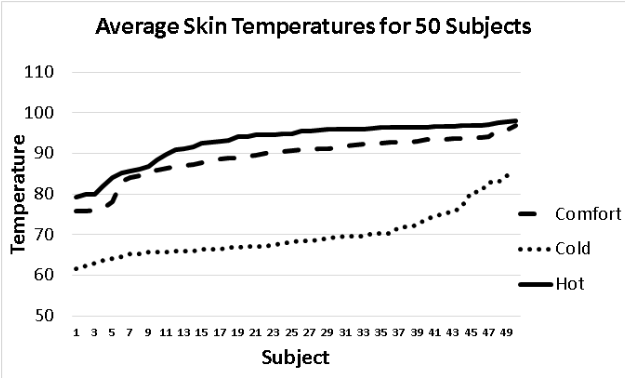

Figure 2: Sorted average temperatures of the 50 subjects through the comfort, cold discomfort, and hot discomfort stages.

from the cold discomfort state to the hot discomfort state. This also indicates that the human body has faster adaptation to heat.

5. CONCLUSION

In this paper, we presented our approach in automatically detecting the thermal sensation of subjects in an enclosed environment similar to that in vehicles. This is a step toward developing technologies that are capable of providing automated climate control without any explicit input from the users.

We presented a novel dataset collected from 50 subjects as well as an approach that utilized four different physiological sensors to detect thermal discomfort. We analyzed the performance of each of these sensors and found that the skin temperature sensor performed the best followed by a combination of all the sensors. The respiration rate sensor and the skin conductance sensor were not good indicators of the thermal discomfort levels of the subjects. Furthermore, it was also shown that our approach was capable of detecting different levels of cold discomfort and hot discomfort separately.

Interestingly, the cold discomfort was detected more reliably than hot discomfort. This is due in part to the human body's built in thermoregulation mechanisms that, in a cold climate, can lower the skin temperature as needed (to reduce heat loss while deploying vasoconstriction) while it will keep its temperature nearly constant when heated (the body's temperature is controlled through sweating and evaporation when the outside temperature is above 37^o C). It was also observed that it took almost double the time to reaching a certain level of cold discomfort compared to hot discomfort. This could be explained using thermoregulation as well as the first law of Thermodynamics. When the human body is being cooled the energy that needs to be expelled from the body is higher due to the metabolic heat production. When the body is heated the metabolic heat does not need to be expelled. This can indicate that humans adapt thermally to heat faster than cold.

There are three directions in improving this research in the future. First, we expect improvement in performance as we extract additional features from the thermal video recordings of the subjects, and integrate them with the physiological sensors features. Second, more instances are needed in order to train our system on separating different levels of cold discomfort and hot discomfort. Third, additional time needs to be added for the heat discomfort stage in order to have reasonable separation from the comfort level, taking also into consideration that the hot discomfort simulation was conducted right after the cold discomfort.

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