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Utilizing Wearable Devices To Design Personal Thermal Comfort Model

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Utilizing Wearable Devices to Design Personal Thermal Comfort Model

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ABSTRACT

Apart from the common environmental factors such as relative humidity, radiant, and ambient temperatures, studies have confirmed that thermal comfort significantly depends on internal personal parameters such as metabolic rate, age, and health status. This is manifested as a difference in comfort levels between people residing under the same roof, and hence no general comprehensive comfort model satisfying everyone. Current and newly emerging advancements in state of the art wearable technology have made it possible to continuously acquired biometric information. This work proposes to access and exploit this data to build personal thermal comfort model. Relying on various supervised machine-learning methods, a personal thermal comfort model will be produced and compared to a general model to show its superior performance. In this work, it has been shown that the introduction of galvanic skin response (GSR) data in training the models results in more reliable and accurate private models.

1. INTRODUCTION

Nowadays, in the developed countries, people spend more than 90% of their time in indoor spaces (Frontczak and Wargocki 2011), (Höppe and Martinac 1998). Most of these indoors are conditioned with different types of HVAC systems that consume 50% of primary energy in the building (Pérez-Lombard, Ortiz, and Pout 2008) to ensure occupant thermal satisfaction (Wagner et al. 2007) and health (Allen et al. 2015). The impact of thermal satisfaction (Leaman and Bordass 1999; Salonen et al. 2012) on productivity in workplaces has made residential and commercial building designers to make comfort a design requirement of high priority. To ensure the criteria for the thermal comfort during the design and operation of the buildings, different types of standards and guidelines are usually used (EN 2007; Iso 2005). The ASHRAE Standard 55 is the most popular one that is utilized extensively in the United States.

Predictive Mean Vote (PMV) and adaptive comfort models are the two primary models used in the most of thermal comfort standards. In PMV Model (Fanger and others 1970), there is a mathematical equation using the personal and environmental information to calculate the thermal comfort. This model is the default thermal comfort model. On the other hand, the Adaptive comfort model (De Dear et al. 1998) uses a linear regression of acceptable indoor operative temperatures. While both models are designated to satisfy the 80% of occupants, both models have some limitations. For example, none of these models supports variables such as gender or age. Moreover, the PMV model needs some expensive sensors to capture data for the airspeed or metabolic rate. On the other hand, some studies

(Auffenberg, Stein, and Rogers 2015; Van Hoof 2008) showed that the accuracy of these models for the small group of occupants is poor. Therefore, there is a need for a new comprehensive thermal comfort model.

The key for a new thermal comfort model is a model that can account for the individual thermal choice in different conditions. The study (Kim, Schiavon, and Brager 2018) reviewed the relevant papers to the new development in comfort modeling during the last ten years, and categorized the researches into two groups. The first one is a data-driven approach to model and predicts thermal comfort of a general population(Chen, Wang, and Srebric 2015; Dai et al. 2017) and the second group is using the synthetic data to model personal comfort (Ari et al. 2008; Peng and Hsieh 2017). For the model output, most studies used the 3-point thermal preferences (warmer/no change/cooler) or ASHRAE 7-point thermal sensation scale. Almost the majorities used indoor air temperature, mean radiant temperature, and relative humidity in their dataset while they tried to gather the individual information such as metabolism and rated skin temperature using wearable devices (Hasan, Alsaleem, and Rafaie 2016).

In our recent study (Rafaie, Alsaleem, and Holthaus 2017), we have developed a machine-learning general thermal comfort model that utilizes the wearable device data (heart rate and skin temperature) along with other parameters such ambient temperature for multiple occupants. In this paper, we expand our approach to create a personal thermal comfort for each occupant, and prove how adding galvanic skin response (GSR) sensor to the wearable device data can improve the performance of both the personalized and general models. The organization of the paper is as follows. In section 2, we introduce the methodology used including dataset manipulations as well as the employed machine learning algorithms. In section 3, the obtained results are presented and discussed. In section 4, we summarize the paper and provide some conclusions.

2. METHODOLOGY

In order to develop the personalized thermal comfort model, we designed an experiment where participants carry a wearable device and a wireless temperature/humidity sensor. A mobile application was implemented to collect the wearable device biometric data, wireless sensors data, and participant votes. The collected data were pre-processed and cleaned before the application of different machine learning classifiers. Figure 1 summarizes the flow of the data/tasks in this experiment, and in a similar order, the following sub-sections explain each task in great details.

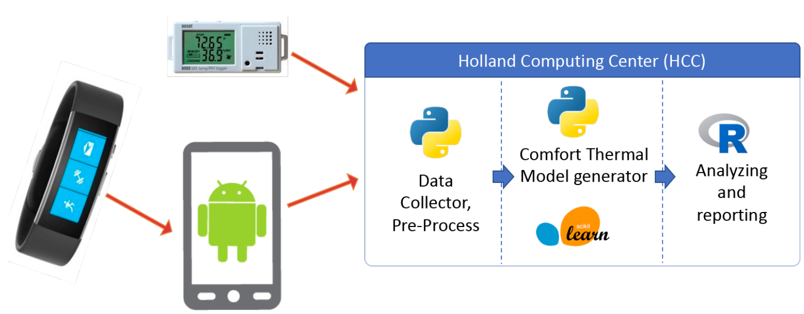

Figure 1: The flow of the data/tasks in this exercise

2.1 Experiment set-up

Three individuals were invited to take part in this study. These individuals were periodically prompted to vote for their thermal comfort throughout the day. This prompt comes through their smartphones as shown in Figure 2. Voting scale was initially from -6 to 6, with 6 being very hot, -6 being very cold, and 0 being comfortable. While this scale offers a large amount of variation, it was determined that people struggle to distinguish between minimal differences on this scale such as that between 5 and 6, introducing unnecessary human error. For this reason, an alternative scale was created as shown in Table 1. In this scale, the values from +/- 6 to +/- 2 were classified as +/- 1 respectively, while values from -1 to 1 were classified as 0.

Table 1: Three Group Definition Vote

	Situation	Scaled vote	Vote Range
1	Hot	+1	-6 to -2
2	Normal	0	-1 to 1
3	Cold	-1	2 to 6

In addition to voting, these individuals were also given a Microsoft Smart Band 2 to be worn and Hobo Data Logger UX100 as the wireless temperature and humidity sensors to be carried throughout the day. An android application called Comfort Vote is developed to run two concurrent tasks, user feedback and sensor data collection. The use feedback task is the main task and participants could enter their comfort vote, clothing details and location during this task. The sensor data collection task collects the bio-information, as shown in Table 2, in a configurable schedule and stores them in the local database.

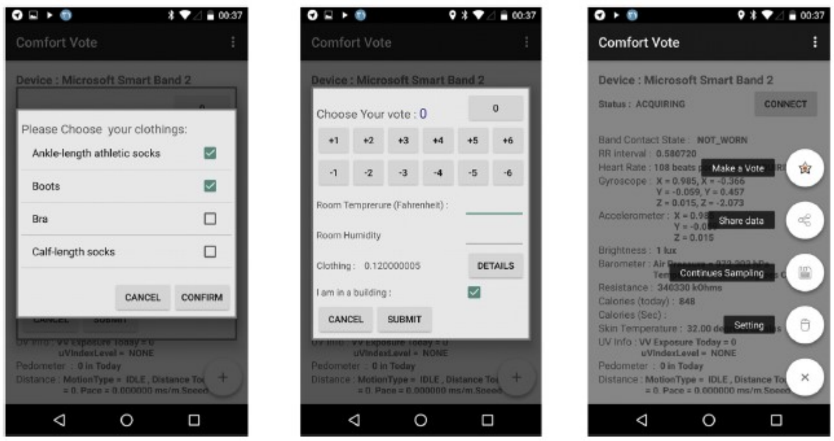

Figure 2: The Comfort Vote mobile application. The first screenshot form left is for collecting the clothing information. The second one is displaying the voting page, and the last one presents the available options in the application.

Table 2: list of data collected from the Microsoft Smart Band 2.

	Sensor Data	Details
1	Accelerometer	Provides X, Y, and Z acceleration in g units
2	Gyroscope	Provides X, Y, and Z angular velocity in degrees per second units
3	Distance	Provides the total distance in centimeters
4	Heart Rate	Provides the number of beats per minute
5	Pedometer	Provides the total number of steps the wearer has taken.
6	Skin Temperature	Provides the current skin temperature of the wearer in degrees Celsius.
7	UV	Provides the current ultraviolet radiation exposure intensity.
8	Band Contact	Provides the current state of the Band as being worn/not worn.
9	Calories	Provides the total number of calories the wearer has burned
10	Galvanic Skin Response	Provides the current skin resistance of the wearer in kohms
11	RR Interval	Provides the interval in seconds between the last two continuous heartbeats

2.3 Machine learning algorithms

Five of the most prominent machine learning algorithms were applied to create three personalized models for each occupant and one general model for the combined data for the three occupants as described in Tabel 3. The used machine learning algorithms are decision tree: (Ligeza 1995) and (Quinlan 2006), adaboost classifier: (Ligeza 1995), (Freund and Schapire 1997), gradient boosting classifier (Mason et al. 1999),(Vezhnevets and Barinova 2007), random forest classifier (Ho 1998; Ligeza 1995; Tin Kam Ho 1995), and support vector vachines (Ligeza 1995) , (Chang et al. 2010). To evaluate the accuracy of these machine learning algorithms we used the Cross-validation method (Kohavi 1995; Ligeza 1995).

Table 3: Occupants data description

	Model	Gender	Age	Data size
1	Person 1	Male	20	54
2	Person 2	Male	24	91
3	Person 3	Female	21	143
4	General	-	-	286

3. RESULTS

This section discusses the performances of the applied machine learning algorithms along with the relevance of some features in determining an accurate comfort model. It is already known that the human skin temperature is the most salient feature that defines the thermal comfort level. However, while doing this work, it has been observed that the galvanic skin resistance (GSR), also referred skin conductance, which usually is ignored in comfort modeling, plays a vital role in improving the accuracy of both the general and private models. However, it should also be noted that skin conductance change is an overall reaction in a subconscious level as a result of many human cognitive and emotional states, not only a manifestation of thermal comfort changes.

Figure 3 to Figure 7 compare the performance of the generalized comfort model with the personalized comfort model for each occupant for each of the five machine learning methods while varying a model parameter in the machine learning method and considering the following features: the skin temperature, skin conductance, room temperature, metabolism rate, clothing, heart rate, and room humidity. Moreover, to study the significance of the skin conductance, models with and without it have been developed and presented in each figure. The figures shows the following:

- The accuracy of the personalized models are in most cases higher than the general model
- Including the GSR sensor data improves both the personalized and general models accuracy
- The random forest classifier exhibits the best accuracy of about 88% compared to other machine learning algorithms

The figure results are also summarized in Table 4.

Figure 3: Decision Tree performance

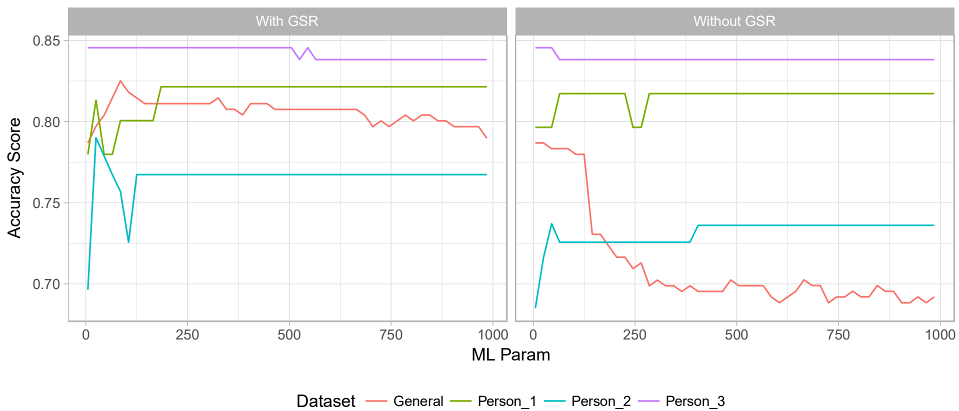

Figure 4: AdaBoost classifier performance

Figure 5: Gradient Boosting classifier performance

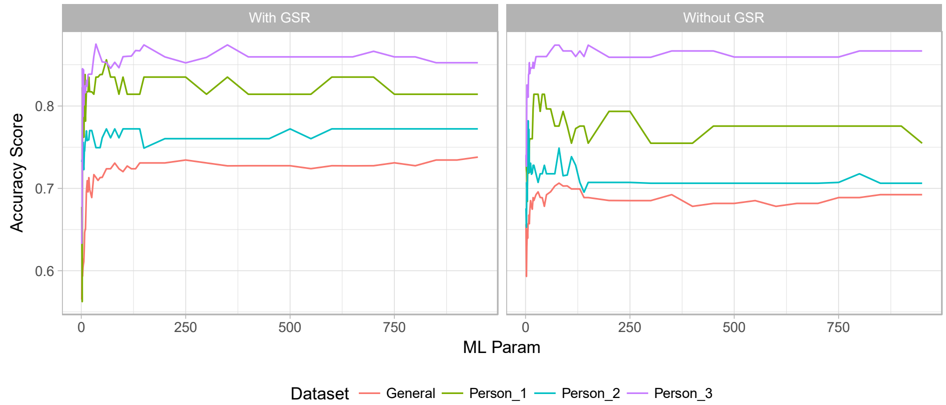

Figure 6: Random Forest classifier performance

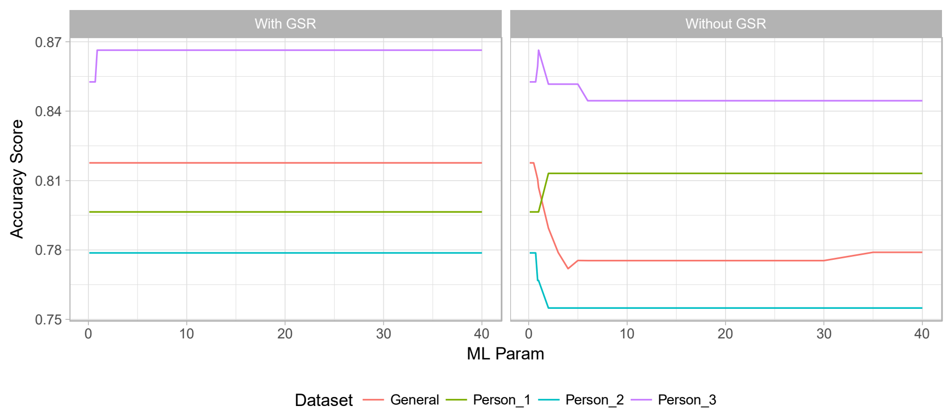

Figure 7: Support Vector Machine with RBF kernel performance.

Table 4: Details of the performance review of Machine Learning for all the datasets

Dataset	Machine Learning Type	Include GSR	Max Accuracy	Min Accuracy	Mean Accuracy
General	AdaBoost classifier	Yes	0.8251	0.7868	0.8060
		No	0.7868	0.6883	0.7111
	Decision Tree	Yes	0.8212	0.5964	0.6550
		No	0.8176	0.5898	0.6113
	Gradient Boosting Classifier	Yes	0.7021	0.6280	0.6560
		No	0.6324	0.5334	0.5444
	Random Forest Classifier	Yes	0.7379	0.5650	0.6994
		No	0.7063	0.5931	0.6804
	Support Vector Machines - RBF	Yes	0.8176	0.8176	0.8176
		No	0.8176	0.7719	0.7838
Person 1	AdaBoost classifier	Yes	0.8214	0.7798	0.8167
		No	0.8173	0.7964	0.8152
	Decision Tree	Yes	0.7976	0.7202	0.7259
		No	0.7964	0.6643	0.6747
	Gradient Boosting Classifier	Yes	0.8393	0.8185	0.8385
		No	0.7768	0.7560	0.7685
	Random Forest Classifier	Yes	0.8560	0.5625	0.8130
		No	0.8143	0.6839	0.7683

	Support Vector Machines - RBF	Yes	0.7964	0.7964	0.7964
		No	0.8131	0.7964	0.8102
Person 2	AdaBoost classifier	Yes	0.7901	0.6963	0.7656
		No	0.7370	0.6850	0.7312
	Decision Tree	Yes	0.7475	0.6514	0.6561
		No	0.7475	0.6275	0.6416
	Gradient Boosting Classifier	Yes	0.7361	0.7044	0.7058
		No	0.6726	0.6606	0.6624
	Random Forest Classifier	Yes	0.7721	0.7227	0.7599
		No	0.7821	0.6528	0.7153
	Support Vector Machines - RBF	Yes	0.7787	0.7787	0.7787
		No	0.7787	0.7549	0.7583
Person 3	AdaBoost classifier	Yes	0.8455	0.8382	0.8421
		No	0.8455	0.8382	0.8386
	Decision Tree	Yes	0.8320	0.7804	0.8211
		No	0.8459	0.8244	0.8436
	Gradient Boosting Classifier	Yes	0.8586	0.7881	0.8295
		No	0.8447	0.7959	0.8230
	Random Forest Classifier	Yes	0.8751	0.6326	0.8410
		No	0.8739	0.7269	0.8510
	Support Vector Machines - RBF	Yes	0.8664	0.8527	0.8648
		No	0.8664	0.8445	0.8473

4. CONCLUSIONS

An improved private comfort model has been developed from biometric data gathered via wearable devices. Apart from skin temperature, skin conductance has been introduced and it has been observed that it is an important feature in creating a private comfort model. Moreover, the difference in the three private models of the individuals presented in this work shows that it is hard to have a general model representative of everyone's comfort state, despite their common physical location. Limited data size contributes to the inaccuracies of the models.

The source code of the project is available https://github.com/rafaie/personal_comfort and the Source of Comfort Vote, the mobile application used to collect the data is in https://github.com/rafaie/comfort-vote

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