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Developing Personal Thermal Comfort Models for the Control of HVAC in Cars Using Field Data

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Abstract: Personal comfort models predict an individual's thermal comfort instead of the average response for a large population. We attempted to develop personal comfort models for car drivers using data collected from 10 cars while driving for approximately 2,000 hr. We measured conditions collected by the CAN-bus (Controller Area Network), a data acquisition system that is present in most of the modern cars. Data includes information about the in-vehicle thermal conditions, the surrounding environment, the status of the Heating, Ventilation, and Air Conditioning (HVAC) system, and the behavior of the occupant. The objective of the study is to assess the feasibility of inferring occupant's thermal preference from the data available already available in most cars. By selecting and filtering all the available signals that are relevant for comfort, in this study we map the user actions of turning on/off their seat heating and correlate them to the vehicle indoor and outdoor conditions. The presented study provides the basis for using a machine learning automated process for thermal self-regulating HVAC system with the aim to improve comfort conditions and safety.

Keywords: Thermal comfort, Personal comfort model, Machine learning, User behavior, Personal comfort systems.

1. Introduction

Reaching satisfactory thermal comfort conditions in cars is a complex subjective process that may requires many adjustments. The continuously changing environment that a moving vehicle is encountering and the fluctuating outdoor conditions cause inhomogeneous and highly dynamic indoor conditions. The thermal regulation systems implemented in cars is often controlled only on air temperature and it may require several control actions from the driver and passengers. Automatic climate control systems are often ineffective in providing satisfying comfort levels. Those systems are usually force air systems making them highly instable in a continuously changing environment (Hausladen et al. 2004). Moreover, thermal comfort cannot be evaluated and achieved only in terms of temperature control, as it is influenced by other parameters such as radiant heat, metabolic rate, airspeed, and clothing insulation (Kim et al., 2018a and b).

While comfort conditions in buildings have been a widely explored topic, thermal comfort in cars has encountered growing interest, particularly in relation to problems of asymmetric conditions and in the context of electric mobility due to the high impact of conditioning system on the battery autonomy (Mebarki et al., 2014; Zhang et al., 2014; Fiori et al. 2016). In addition, modelling radiation and energy fluxes in a vehicle that moves through varying weather conditions requires the computation of a high number of variables, making the simulation models very complex.

To avoid the complex modelling, the present study focuses on the relationship between the user behavior and thermal conditions. Pervasive collection and analysis of car sensory data is made possible through the CAN-bus (Controller Area Network) (Kiencke et al., 1986) technology that provides almost real-time information about the car, the driver and the surrounding environment. Each modern car, in fact, contains more than 2,000 sensors constantly producing data that open up the possibility to capture some of it to map user behavior and the thermal environment with a high resolution.

Personal comfort models are built from analyses derived from such data and designed to predict an individual's thermal comfort response, instead of extrapolating related assumptions derived from the average response of a large population (Kim et al. 2018b). They have a much higher predicting power than PMV and adaptive personal comfort models can be based on environmental parameters (e.g., air temperature) (Cheung et al., 2017), occupant feedback and behaviour (Kim et al. 2018a), occupant behaviour and measured physiological parameters (e.g., skin temperature, heart rate) (Liu et al. 2018).

Currently, comfort is typically achieved in cars as a result of occupants adjusting internal thermostats as conditions change. The present study aims at assessing the feasibility of developing personal comfort models based on CAN-bus signals, particularly concentrating on the seat heat. If successful, this approach would allow for a personalized automated thermal control in vehicles designed to improve comfort conditions and safety, automating HVAC adjustments basing on a high number of environmental control variables.

2. Methodology

CAN-bus technology is a standard bus that allows fast and reliable communications among all electronic components in cars. The possibility of leveraging the CAN-bus technology to couple human and environmental sensed data for predicting and studying human behavior has been proposed and analyzed for several applications (Massaro et al., 2017). With the aim of developing a personal comfort model based on CAN-bus signals, this study was based on the use of selected signals generated by actions that the user undertakes in order to influence thermal comfort conditions.

Personal models, traditionally, are based on the PMV model (Predicted Mean Vote) (Fanger et al., 1970) that requires six layers of information: air temperature, mean radiant temperature, relative humidity, air speed, clothing factor and metabolic rate. Figure 1 gives a chart that synthetizes the functioning of the model. The PMV model is a steady state model, therefore it does not consider the dynamics of the phenomenon. Furthermore, the implementation of the PMV model requires high accuracy in the input variables that are strongly related to the users, such as clothing insulation and metabolic rate, which are therefore assumed or simplified and cannot be updated to reflect the actual comfort conditions of individuals in a complex setting (Kim et al., 2018a).

The proposed model considers as input variables a subset of the CAN-bus data, which can be divided in three categories: user's actions on the HVAC system; user actions on car components that influence the personal comfort (such as windows and shades); other environmental variables (such as temperature).

The drivers did not answer to thermal comfort surveys, therefore, thermal comfort was inferred from their actions. We recognize that this is a limitation. The basic principle that we assumed is considering user actions as moments in which thermal comfort is not achieved, and thus actions are triggered in order to change the car's climate condition. Therefore, analyzing those actions and the corresponding environmental variables (

Figure 1) – including the evolution of the variables up to the action's moment – personal patterns in terms of comfort achievement could be inferred. Basing upon those patterns, the model can be used with a predictive approach, predicting the next user action given historical actions and environmental variables (Figure).

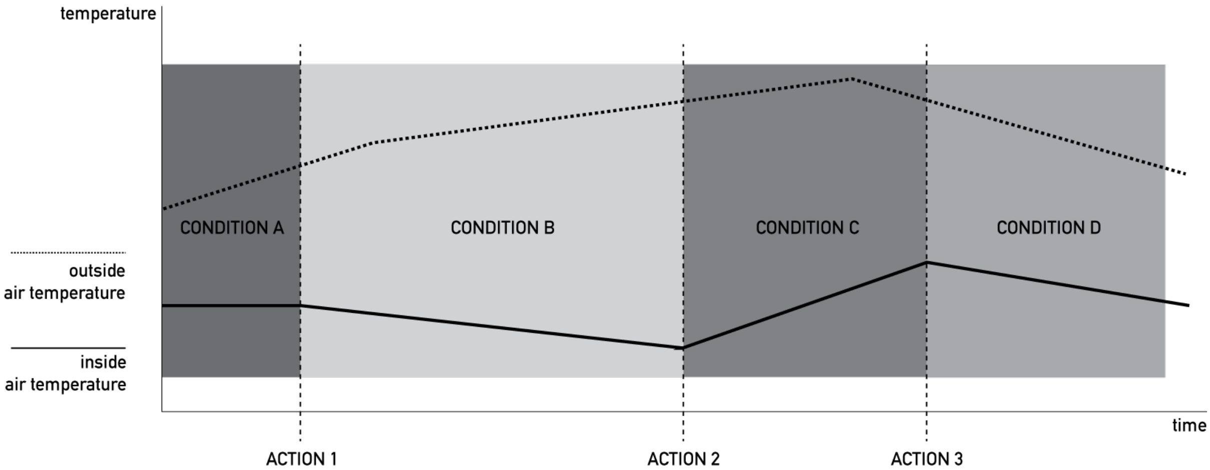

Figure 1 – Example of user actions and environmental variables change.

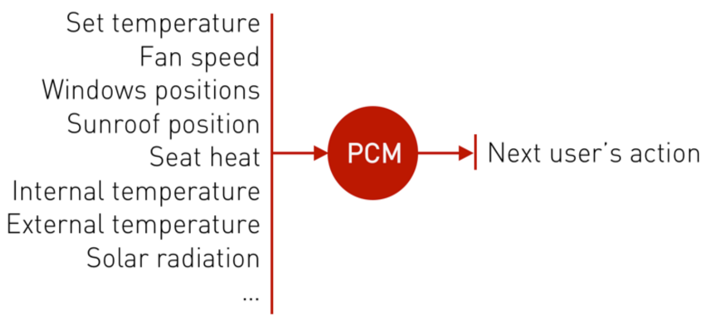

Figure 2 – Structure of a Personal Comfort Model (PCM)

In particular, the proposed personal comfort model – which boils down to a machine learning predictive algorithm – is composed of two phases (Figure). The first is an initial training phase, where user actions are monitored and rules and non-linear relations are inferred. The second is an *autonomous real-time phase*, where rules learnt in the first phase are applied to external variables in order to predict the user actions and, ultimately, change HVAC settings accordingly.

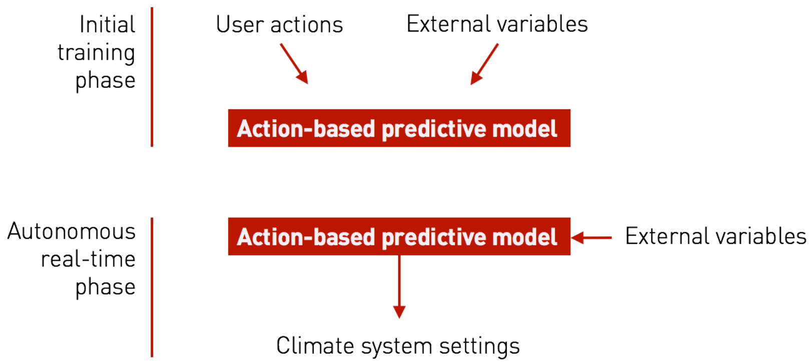

Figure 3 – Conceptual phases of the PCM machine learning model.

3. Dataset

3.1. Experimental settings

The data acquisition took place in 2014 by Audi AG and Audi Electronics Venture in Ingolstadt, Germany. 10 different cars have been retrofitted with a data-logger and more than 2,000 CAN-signals have been recorded. A total number of 53 drivers have been involved in the data collection, providing a rich dataset of more than 2,135 hours of driving over 55 d of experiments. No personal information about the drivers has been recorded.

Cars were picked up by the drivers in a central deposit and had to be returned within the same day. Each time a user switched on the car engine, the computer registered a new session. A total of 1,987 sessions were recorded; each user drove an average of 31 sessions, with an average duration of 64 minutes per session. Figure 1 plots the durations of sessions for each driver. Data has been recorded for 55 days in the months of March, April and May 2014 during weekdays. Figure 2 shows the temporal distribution of data acquisitions for each car. Meteorological conditions were various during the experiment, with several days of rain and external temperatures ranging between -3 and 24 °C[1].

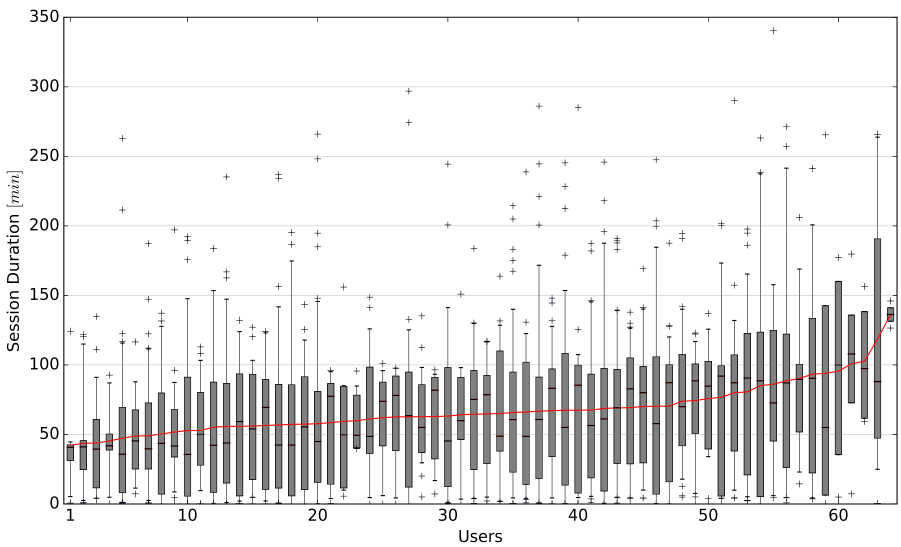

Figure 1 – Sessions duration for each user, sorted by their mean value (red line).

[1] Data retrieved from Weather Underground, https://www.wunderground.com, station IBAYERNIK12.

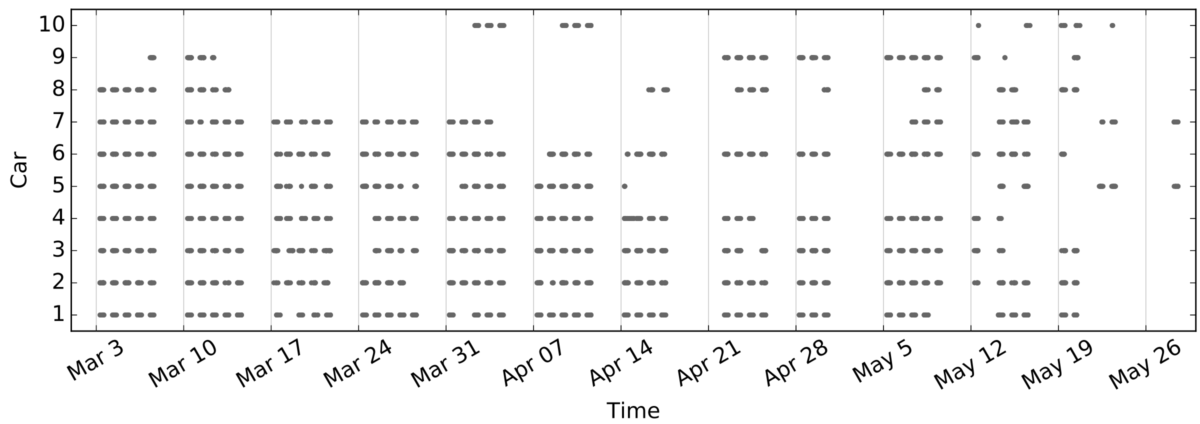

Figure 2 – Sessions distribution over time for each car.

3.2. Data structure, filtering and preprocessing

The database contains the complete set of signals form the CAN-bus, a wide spectrum of information that tracks different communications among components in the vehicle and for different purposes. A summary of the high-level information available in the CAN-bus useful for a climate comfort model can be found in Table 1. For windows statuses, we had information about both driver's and passenger's window being opened or closed. Moreover, we had records whether it is raining and also what is the wiper speed. The position of the sunroof blind is telling us whether it is sunny or not. Finally, in this study we only focused on user action of turning on/off driver's seat heat.

Table 1 – List of used signals in the study.

Signal information	Taxonomy area	Data type	Raw table cardinality
Driver's window opened	Windows and shades	Boolean	10,462
Passenger's window opened	Windows and shades	Boolean	6,700
Sunroof blind stage	Windows and shades	Boolean	5,200
Windshield wiper active	Rain	Boolean	18,488
HVAC system on/off	HVAC	Boolean	25,700
AC compressor on/off	HVAC	Boolean	7,355
Driver's seats heat levels	HVAC	integer	6,707
Internal temperature	Environment	float	250,641
External temperature	Environment	float	116,935

The datatype of the signals recorded is Boolean (i.e. on/off), integer or float, and their sizes vary from a few MB to a few GB for each sensor. The signals are not uniformly sampled, i.e. the time difference between each sample of the physical quantity is not constant. This is due to the nature of the sensor system that was designed to sample the quantity only if there were a minimal variation with respect to the previous sampled value. In this way, the size of the database does not increase linearly with time and disk space is optimized.

We preprocessed the data after we retrieved the raw data from the database. Although it was said that the record of sampling was saved only if there was a minimal variation with respect to the previous sampled value, the dataset contained consecutive records with the same values, which had to be filtered first. Outlier filtering was also performed on the internal temperature signal, as very often the initial value when a new session would start was -40 °C degrees.

The focus in this paper is on user action of turning on/off their seat heat; therefore, we produced a histogram of the values (Figure). The dataset contained 50 records (about 1.5%) with values larger than 120 min, 30% of values that change under 1 min and 42% of values that changes under 3 min. We decided to omit all records that changed under 3 min, which left us in total with 2,320 records of user's actions.

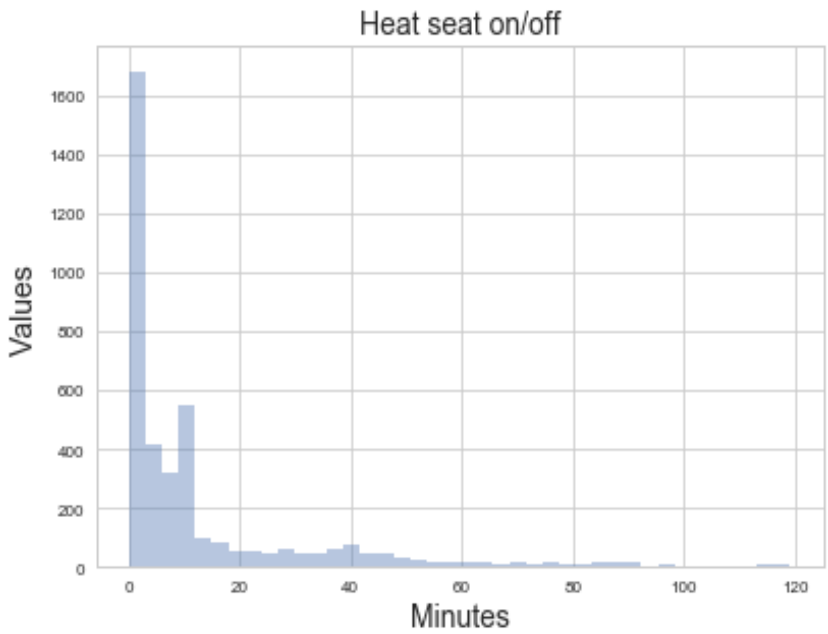

Figure 6 – Histogram showing how often user action of turning on/off seat heat is occurring.

After cleaning the dataset, we performed the last step of preprocessing in which we overlaid user action of turning on/off seat heat with the aforementioned vehicle indoor and outdoor conditions. As previously mentioned, as signals were not collected synchronously, for each user action we had to find the closest match in other tables, i.e. the record that occurred in approximately the same time window. However, we did not include values that were too much apart from each other, so we used a threshold of three minutes. This means that we would add to the specific user action of turning on/off their seat heating the corresponding value from other tables only if the record in the second table was made either three minutes before the user action or after, otherwise we would dismiss both records from our further analysis. Finally, if we would find more than one value in the second table within three minutes before/after the user action, we would take the one that was made at time that was closer to the time of the original user action.

4. Analysis

In order to determine possible recurrent co-occurrence relationships among different signals, a first analysis was carried out to determine the correlation between pairs of samples. The analysis concentrated on all couples formed by the internal temperature, the external temperature and the driver's seat in association with other signals, namely HVAC system status, AC compressor status, driver's and passenger's windows, windshield wiper. The correlation is expressed using the Pearson's correlation coefficient, ranging from -1 to 1. The complete list of the analyses results is reported in Table 2.

Table 2 – Correlation coefficients between driver's seat heating and other signals.

Signal 1	**Signal 2**	**Correlation coefficient***
Internal temperature	HVAC system on/off	**0.10**
	AC compressor on/off	**0.12**
	Driver's window position (open/closed)	0.01
	Passenger's window position (open/closed)	-0.05
	Windshield wiper	-0.08
External temperature	HVAC system on/off	0.04
	AC compressor on/off	0.09
	Driver's window position (open/closed)	-0.03
	Passenger's window position (open/closed)	**-0.10**
	Windshield wiper	-0.02
Driver's seat heating	HVAC system on/off	**0.42**
	AC compressor on/off	**0.46**
	Internal temperature	-0.04
	External temperature	-0.06
	Driver's window position (open/closed)	**-0.21**
	Passenger's window position (open/closed)	**-0.21**
	Windshield wiper	**0.36**

* Correlation coefficients above 0.1 are bolded

Results show higher correlations of the driver's seat heating with the HVAC system status, the AC compressor status and the windshield wiper. This means that high values of seat heat usually correspond to HVAC, AC in heating mode and wipers status on. A slightly weaker correlation occurs between the driver's seat heating and the window positions (not surprisingly, negative correlations, i.e. if the seat heat level is high the window is closed, and vice versa), while there are no significant correlations among other signals.

A further investigation has been carried out to visually inspect the variability of non-categorical variables (internal and external temperature) with the driver's seat heating level. In Figure 73, boxplots confirm the non-correlation between the seat heating level and internal or external temperature; for this reason, these variables cannot be used to control the car heating system

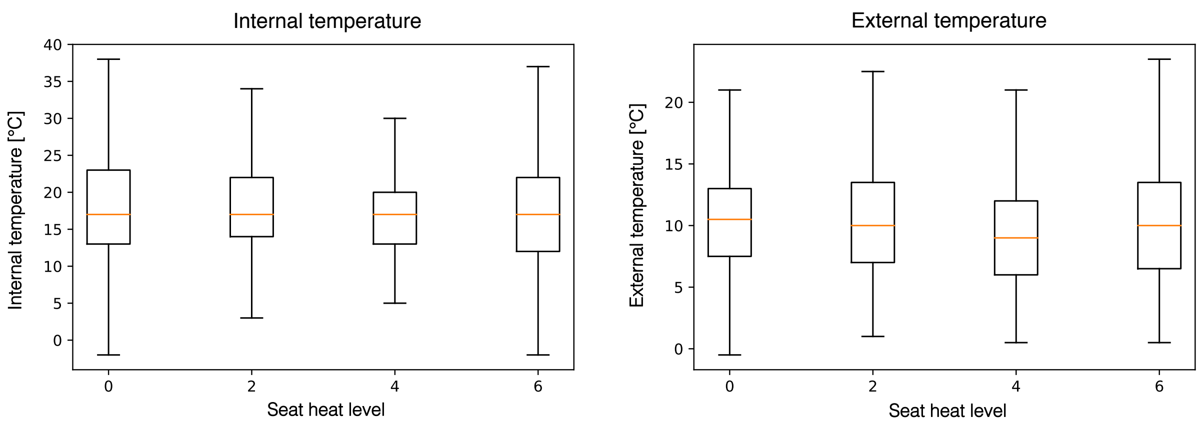

Figure 73 – Internal and external temperatures distributions for different levels of driver's seat heating.

Basing on the promising correlation results, more sophisticated models are needed in order to investigate possible non-linear relations between signals and user actions. Suitable machine learning methods could be Artificial Neural Networks (ANN), Support Vector Machines (SVM), regression trees or random forest models (Hastie et al., 2009). In this work, considering the preliminary exploration phase of the database, experimental data were analyzed using a regression tree model.

Following the scheme explained in Figure , the model has been trained with vectors containing values of the variables in Table 1, except for the seat heating that was considered as the label object of inference. For simplicity, the seat heat level was considered as a Boolean variable, mapping the value 0 to *false* and 2, 4, 6 to *true*.

The model implemented did not show satisfactory results (R^2 close to zero). This is due to a combination of different factors, such as: the high number of missing values among the matched signals, as mentioned in the preprocessing paragraph; the low amount of datapoints in the database; the low variability in overall weather conditions and user's perception due to the middle-season months in which the experiment has been carried out (March-May), the fact that people on the cars for the first time might have unintentionally pressed on some controls. Overall the data set, although apparently valuable, proved to be not sufficiently comprehensive to establish statistically significant prediction relationships between the considered variables. Given this limitation, the authors are not confident in the model's results at the present stage and general conclusions cannot be drawn from this paper's specific implementation. We think that with a properly designed thermal comfort experiment and the presence of driver thermal comfort preference survey as ground true, it is possible to create personal and group comfort model with high predicting power.

5. Conclusions

This paper attempted to develop a personal comfort model to be applied for the control of HVAC in vehicle using real data collected from the CAN-bus. The personal comfort paradigm has been applied to in-vehicle comfort and an analysis of the signals that could be used for achieving this goal has been carried out. Moreover, a preliminary data analysis has been performed on experimental data, showing a good correlation between the seat heating and other signals; on the other hand, no significant correlation has been found between seat heating level and internal or external temperature. However, after the proposed model was implemented, we did not get satisfying results. Therefore, in future work, the presented model should be further tested with bigger dataset acquired in more various and extreme climatic conditions, occupant thermal preference should be collected and a fine-tuning of the model's parameters will be required in order to train it on more complex datasets.

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