Comfort in Cars
Estimating Equivalent Temperature for Comfort Driven Heating, Ventilation and Air Conditioning (HVAC) Control

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Abstract: Equivalent Temperature is generally considered an accurate predictor for thermal comfort in car cabins. However, direct measurement of this parameter is impractical in fielded applications. The paper presents an empirical, multiple linear regression based approach for estimating body segment equivalent temperatures for car cabin occupants from different sensors within the car. Body part equivalent temperature at eight segments and cabin sensor data (air temperature, surface temperature, mean radiant temperature, humidity and solar load) was gathered in a variety of environmental and cabin conditions. 38 experimental hours of trials in a controlled environment and 26 experimental hours of realistic driving trials were used for training and evaluating the estimator's performance. The estimation errors were on average between 0.5 °C and 1.9 °C for different body parts for trials within a controlled environment, while for trials in realistic driving scenarios they ranged between 1 °C and 2 °C. This demonstrates that passenger body part equivalent temperature can be estimated using a multiple linear regression from environmental sensors and leads the way to comfort driven Heating, Ventilation and Air Conditioning control.

1 INTRODUCTION

Car buyers expect that climate control systems will make them comfortable. In order to control comfort and not merely climate temperature, one must first be able to estimate it. Estimating comfort, however, is acknowledged to be a difficult task given that the cabin is a rapidly changing environment, non-uniform with respect to parameters such as air temperature, air velocity and solar load. Furthermore, current Heating, Ventilation and Air Conditioning (HVAC) systems are power hungry and thus not well suited to electric vehicles as they may substantially reduce the vehicle's range.

In order to enable efficient control we need a better understanding of the relationships between environments and perceived comfort levels. Prior work established that Equivalent Temperature (ET) can be an accurate predictor for comfort (Mayer and Schwab, 1999), (Curran *et al*., 2010), (Mola *et al*., 2004). Dry heat loss transducers allow in-field calculation of ET (Madsen *et al*., 1986), however they are too large and costly to be used in a production car. An alternative approach is clearly needed.

In this paper, we propose a method for estimating ET at several body locations for cabin occupants, based on easily measured cabin variables, such as air temperature and mean radiant temperature. The method requires only a small number of cheap sensors placed within the car and accounts for the dynamic nature of the cabin environment. The method can be used to perform estimation in real-time and is intended to lead to high performance HVAC control systems which can be optimized for energy usage in low carbon vehicles.

The main contributions of this paper are: 1) to demonstrate an ET estimation method that requires non-expensive and non-intrusive sensors, 2) optimisation of the estimation method through sensor location selection based on Mutual Information and 3) validation of the method on data gathered in a variety of conditions, from controlled trials in stable environments to daily driving trials. Although the results here are specific to environmental conditions found within car cabins, the method itself is applicable to other environments, given appropriate empirical data.

The paper is structured as follows: Section 2 reviews related work in the area of remote estimation

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of a range of parameters. Section 3 describes the experimental data sets gathered for evaluation purposes, while Section 4 presents the multiple linear regression ET estimation method. Section 5 presents the results obtained through training and testing the estimator. Finally, Section 6 concludes the paper.

2 RELATED WORK

Traditionally, vehicle HVAC systems control cabin air temperature and humidity to a target set-point. However, it has long been established that thermal comfort is influenced by a variety of factors in addition to air temperature, such as mean radiant temperature, relative air velocity, relative humidity, metabolic rate and clothing thermal resistance (Fanger, 1973), (Gagge *et al*., 1967). Moreover, it is known that occupants feel comfortable over a range of temperatures rather than at one specific temperature (Fanger, 1973), (ANSI/ASHRAE, 2004), (Singh *et al*., 2010). Estimating the level of passenger comfort allows generating the exact amount of energy needed, instead of wasting additional energy by warming-up or cooling-down the whole cabin to a certain set-point temperature. It can therefore be concluded that the traditional approach is not optimal with regards to ensuring comfort and energy efficiency. This indicates that in order to develop improved HVAC control algorithms, there is a need to 1) sense more than just air temperature and 2) utilise thermal comfort estimates for cabin occupants in the control feedback loop.

ET is formally defined as the uniform temperature of the imaginary enclosure with air velocity equal to zero in which a person will exchange the same dry heat by radiation and convection as in the actual non-uniform environment (SAE Journal, 2012). Intuitively, ET corresponds more closely to the human sensation of environmental temperature than air temperature alone. ET is an accurate predictor for thermal comfort (Mayer and Schwab, 1999), (Curran *et al*., 2010), (Mola *et al*., 2004), which integrates the effect of air temperature, mean radiant temperature and relative air velocity. However, its direct measurement can be intrusive, expensive and bulky. An alternative to measuring ET is to estimate it from measurements made at more convenient locations.

A variety of learning based models have been created for the remote estimation of several parameters in different environments. Mehnert *et al*. (2000), for example, used a multiple linear regression to estimate average skin temperature from parameters such as air temperature, mean radiant temperature, air velocity, metabolic rate, rectal temperature and partial vapour pressure. Buller *et al*. (2010) developed an estimator of human core body temperature using Kalman filters, with only heart rate as input. Lee (2007) developed an artificial neural network for car cabin air temperature prediction from 17 inputs, such as direct sun intensity, air temperature outside the car, outside air velocity and ventilation temperature.

Similar to the work presented in this paper, Mola *et al*. (2001) developed an ET estimation model that can be used to control the car cabin environment. A series of trials in a controlled environment were performed to identify the estimator, during which a thermal manikin occupied the driver seat and measured overall ET. The cabin air temperature, HVAC outlet air temperature, external air temperature and mean radiant temperature were also recorded. Of these measured parameters, mean radiant temperature, HVAC outlet air temperature and air velocity were found to allow the best estimate of ET. A linear mathematical expression was inferred for estimating ET. The method was only assessed qualitatively and it was concluded to successfully drive HVAC control. A downside of this method is the fact that only one sensor was used to measure the cabin temperature, while different air temperature sensor locations within the cabin can increase the estimator's accuracy (Hintea *et al*., 2011). Moreover, the data used for training and testing the system came from controlled trials, leaving open the question of how well it would perform in realistic driving scenarios.

There are several gaps in the state of the art that this paper tries to fill: 1) using a large number of sensors for data gathering as this enables optimisation of sensor location (Hintea *et al.*, 2011) and leads to a more efficient estimator, 2) validating the estimator on data gathered in a variety of conditions, not only in stable, controlled environments and 3) quantifying the ET estimation error for multiple occupant body parts, rather than overall.

3 EXPERIMENTAL DATA GATHERING

The training and testing of the algorithm implemented here was based on experimentally gathered car cabin data within a variety of conditions. Throughout all 113 trials, ET was monitored at eight locations (corresponding to head, chest, left lower arm, right lower arm, left upper arm, right upper arm, thigh and calf) using the INNOVA Flatman thermal manikin, shown in Figure 1 (right), positioned in the front passenger seat of the test car. Cabin air and surface tempera-

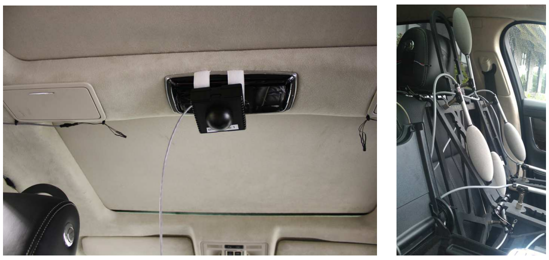

Figure 1: Experimental data gathering. Left: Mean radiant temperature sensor. Right: Upper body of the Flatman thermal manikin.

ture data was gathered using type K thermocouples and was recorded by a Grant Instruments DataTaker DT85 data logger.

Surface temperature was collected at the following locations: left and right instrumentation panel, steering wheel, front row passenger seat back and seat cushion, back row left seat back and seat cushion, left and right windscreen, front row left and right side glazing and back row left side glazing. Air temperature was collected at the following locations: external temperature, front row left and right headrest, front row belt, front row left and right foot, back row left and right headrest, back row belt, back row left and right foot. HVAC vent discharge temperature was collected at the following locations: front row left inner face vent, front row left out face vent, back row left face vent. A total of seven subjects (four males and three females) occupied the driver seat in turn and an observer occupied the rear right seat.

Four types of trials were performed corresponding to two main categories, as described in Sections 3.1 and 3.2.

3.1 Controlled Environment Trials

The trials described in Sections 3.1.1 and 3.1.2 involve controlling the external environment (solar load, ambient temperature, wind) while varying the HVAC control.

3.1.1 Variable Cabin Temperatures within Steady state external conditions (T1)

These trials were performed within an enclosed space, characterized by stable ambient air temperature. Both the subjects and the test car cabin were preconditioned to 22 °C. At the outset of the experiment the subject entered the car and remained in static conditions (same HVAC set-point) for 10 minutes. The temperature was then increased by 1 °C every 3 minutes until it reached 28 °C. The same trial was performed with the HVAC set-point decreased by 1 °C every 3 minutes until it reached 16 °C. The air flow from the HVAC system was set to high or medium settings and trials with and without simulated solar loading on the driver side of the car were performed. The conditions are characterized by interior temperature rates of change less than 1.5 °C per minute, stable outside temperature (less than 1 °C difference per trial) and no wind or precipitation.

3.1.2 User control within Steady State External Conditions (T2)

These trials were performed within an enclosed space, characterized by stable ambient air temperature. The car cabin and the subjects were preconditioned to a neutral (22 °C), hot (28 °C), or cold (16 °C) temperature. The subjects entered the car and remained inside for 15 minutes, during which they were permitted to adjust the air conditioning at will in order to make themselves more comfortable. These trials were performed both with and without simulated solar loading on the driver side of the car. Higher car cabin interior temperature rates of change were encountered (up to 7 °C per minute) with stable outside temperature (less than 1 °C difference per trial) and no wind or precipitation.

3.2 Realistic Driving Trials

The trials described in Sections 3.2.1 and 3.2.2 were aimed at providing realistic driving scenarios within both short and long trips. They involve no control over the external environment (solar load, ambient temperature, wind) while varying the HVAC control.

3.2.1 User Control during Driving within Short Trips (T3)

These trials consisted of subjects driving the test car on private roads. The car and the subjects were preconditioned to a neutral (22 °C), hot (28 °C), or cold (16 °C) temperature. The subjects entered the car and drove for 15 minutes, during which they were permitted to adjust the air conditioning at will in order to make themselves more comfortable. The subjects were required to turn and change speed at frequent intervals in order to simulate to an extent the daily driving routine. These trials were characterized by interior temperature rates of change of up to 6 °C per minute and less stable outside temperature (up to 3 °C difference per trial), alone with ambient wind, solar load and precipitation.

3.2.2 Automatic and User Control during Driving within Long Trips (T4)

These trials consisted of a five day road-trip throughout the UK in a test vehicle. On each day there were four trials, lasting around 2 hours each and differentiated by the HVAC control mode: automatic mode at 20 °C, automatic mode at 22 °C, automatic mode at 24 °C and manual mode. The car cabin instrumentation consisted of the sensors used for the previous three types of trials and an additional set of sensors: mean radiant temperature collected at a center ceiling location, shown in Figure 1 (left); solar load, collected at locations corresponding to dashboard left and right and at the car centre; air temperature, collected at locations corresponding to dashboard left and right. The experimental conditions encountered are characterized by interior temperature rates of change of up to 5 °C per minute and external temperature differences up to 5 °C per trial, along with ambient wind, solar load and precipitation.

Experiment types will be referred in the paper by the *T1*, *T2*, *T3* and *T4* abbreviations.

4 EQUIVALENT TEMPERATURE ESTIMATION METHOD

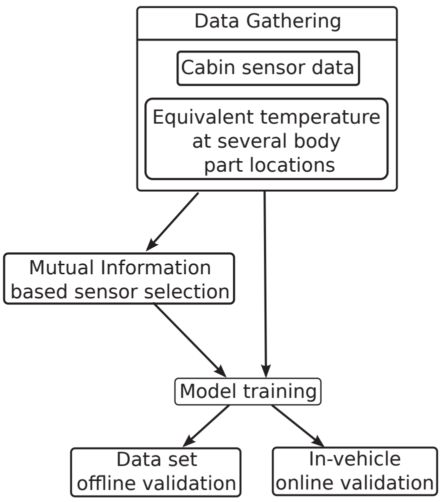

Figure 2: Equivalent temperature estimation method training and validation.

This section describes the method developed to estimate ET at different body part locations from one or more sensors located within the cabin (shown in Figure 2). The first step of the method consists of data gathering (described in detail in Section 3). Building an accurate ET estimation model also relies on the selection of an appropriate set of sensors within the car cabin. Here the sensors are selected through a Mutual Information (MI) based method (described in more detail in Hintea *et al*., 2011).

Given n sensors within the cabin, $S_1, S_2, ..., S_n$, and T_{eq} the ET to be estimated, the MI between them, $I(T_{eq}; S_1, ..., S_n)$, can be written as:

$$I(T_{eq}; S_1, ..., S_n) = H(T_{eq}) - H(T_{eq}|S_1, ..., S_n).$$

The conditional entropy $H(T_{eq}|S_1, ..., S_n)$ can be computed as following:

$$H(T_{eq}|S_1, ..., S_n) = H(T_{eq}, S_1, ..., S_n) - H(S_1, ..., S_n),$$

where $H(T_{eq}, S_1, ..., S_n)$ is the joint entropy for the $n+1$ sensors, while $H(S_1, ..., S_n)$ is the joint entropy for the n sensors used for the estimation.

Finally, MI can be defined as:

$$I(T_{eq}; S_1, ..., S_n) = H(T_{eq}) + H(S_1, ..., S_n) - H(T_{eq}, S_1, ..., S_n)$$

The group of m sensors ($m = 2$ within this paper) that shares the highest MI with the ET over all body parts is selected by maximising the MI over the eight body parts. It should be noted that the sensor locations selected may vary from one vehicle to another.

Multiple Linear Regression (MLR, Draper and Smith, 1981) lies at the core of the ET estimator. The MLR model suitable for this application can be written as:

$T_{eq} = \alpha_0 + \alpha_1 S_1 + \alpha_2 S_2 + ... + \alpha_m S_m$, where T_{eq} is the body part ET being estimated, $\alpha_0, ..., \alpha_m$ are the regression coefficients and $S_1, ..., S_m$ are the sensors previously selected. Training data gathered from the experimental trials described in Section 3 is used to compute the regression coefficients. Due to using k-fold cross validation to evaluate the performance of the estimator, training was performed on k-1 data chunks of the input data set, while testing was performed on the remaining data chunk. This model can be used in a deployed system by continuously estimating the T_{eq} values from real-time measured sensor values $S_1, ..., S_m$.

Several other estimation methods have been applied, such as Multilayer Perceptron (Haykin, 1998), REPTree (Witten and Frank, 2005), K-Nearest Neighbour (Cover and Hart, 1967), Multivariate Adaptive Regression Splines (Friedman, 1991), Radial Basis Function network (Haykin, 1998) and Random Forest (Breiman, 2001). MLR was the third in terms of accuracy, after the Multilayer Perceptron and Multivariate Adaptive Regression Splines methods, however, MLR outperformed the latter in terms of modeling and processing time, while the extra small gain in accuracy is not of significant impact (a lower average error of 0.10 °C on a 5 °C to 35 °C range) .

5 EVALUATION OF THE METHOD ON EXPERIMENTAL DATA

K-fold cross validation was used to evaluate the estimator's performance, both on the full set of experimental data and on separate sets of trials in order to observe the best/worst scenario, indicating how well the algorithm generalizes to unseen data. The outputs of the estimator were compared to the original measured ET and the Root Mean Square Error (RMSE) was used as an accuracy measure.

5.1 Controlled Environment Trials

The MI sensor selection procedure was performed to determine the pair of sensors giving the lowest ET estimation errors over all body parts for trial sets *T1* and *T2*. The sensors selected were the surface temperature sensor located at the back row left seat back and the air temperature sensor located at the back row right headrest level.

As Table 1 shows, the lowest estimation errors were obtained for the trial set *T1*, ranging from 0.5 °C for the thigh to 1.3 °C for the head, averaging 1 °C over all eight body parts. The estimation errors were higher for the trial set *T2*, averaging 1.5 °C and ranging from 1.3 °C for the chest to 1.9 °C for the upper arm. The higher error for the latter could be due to significantly higher car cabin temperature rates of change (up to 7 °C per minute). Figures 3 and 4 show the measured versus estimated ET at the head and thigh level within one trial of *T1* and *T2* (starting from 28 °C and with the HVAC flow set on medium).

Table 1: Equivalent temperature estimation results (RMSE) from the best two sensors in trials *T1* and *T2*.

Equivalent temperature	Trial type *T1*	Trial type *T2*
head	1.33 °C	1.71 °C
chest	0.95 °C	1.38 °C
lower arm	1.05 °C	1.59 °C
upper arm	0.96 °C	1.92 °C
thigh	0.53 °C	1.51 °C
calf	1.28 °C	1.44 °C
average	1.02 °C	1.59 °C

5.2 Realistic Driving Trials

The pair of sensors corresponding to the lowest estimation errors for trial set *T3* was the same as for *T1* and *T2*. However, as Table 2 shows, the estimation errors were higher than for the previous types of trials,

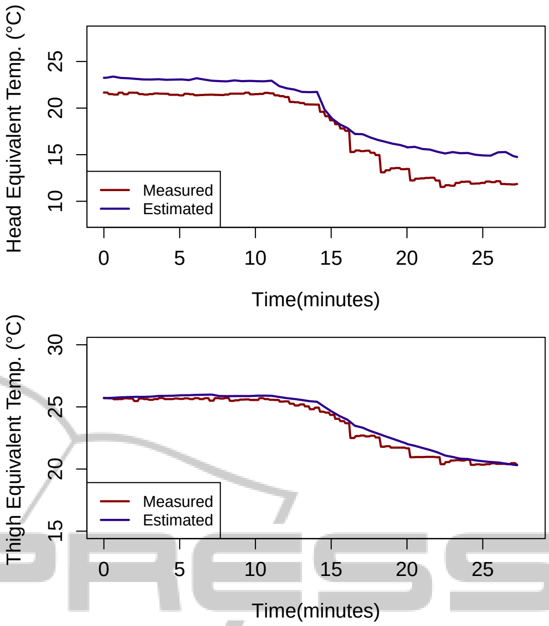

Figure 3: Estimated versus measured equivalent temperature at the head and thigh level during one trial of *T1*.

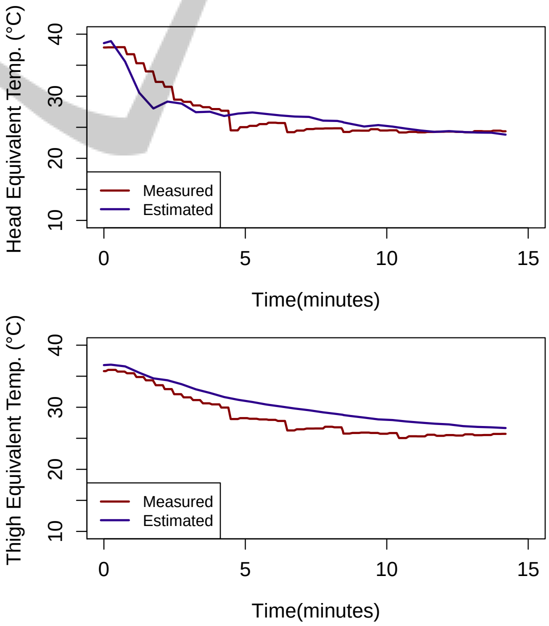

Figure 4: Estimated versus measured equivalent temperature at the head and thigh level during one trial of *T2*.

averaging 1.9 °C over all body parts and ranging from 1.4 °C for the calf to 2.5 °C for the head. The reasons for this could be the high car cabin temperature rates of change (up to 6 °C per minute) and variable external conditions, such as solar load, precipitation and air temperature.

Among other parameters, ET integrates the effect

Table 2: Equivalent temperature estimation results (RMSE) from the best two sensors in trials *T3* and *T4*.

Equivalent temperature	Trial type *T3*	Trial type *T4*
head	2.5 °C	1.44 °C
chest	1.63 °C	1.42 °C
lower arm	2.32 °C	1.29 °C
upper arm	2.01 °C	1.37 °C
thigh	1.63 °C	1.06 °C
calf	1.47 °C	2.08 °C
average	1.93 °C	1.44 °C

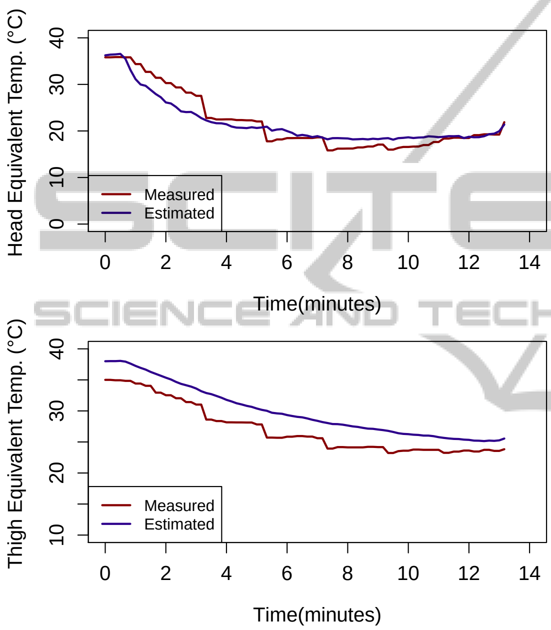

Figure 5: Estimated versus measured equivalent temperature at the head and thigh level during one trial of *T3*.

of mean radiant temperature. The latter was measured within trial set *T4* and was found to relate best to ET. The pair of sensors giving the lowest estimation errors were the mean radiant temperature sensor and the air temperature sensor located at the front row right belt level. The estimation errors for *T4* were lower than for *T3*, most likely due to using the mean radiant temperature as an estimation source. They average 1.4 °C over all body parts, with a minimum error of 1 °C for the thigh and a maximum error of 2 °C for the calf. Interesting to note is that throughout most experiment types the body parts directly exposed to the vent air flows (head, calf and arms) were estimated with the largest error. Figure 5 show the measured versus estimated ET at the head and thigh level within one trial of *T3* (starting from 28 °C and with the HVAC flow set on medium).

Nilsson *et al*. (1999) conducted empirical trials to find the ET ranges for 16 body parts that would correspond to thermal comfort. They found that both in winter and summer conditions, the comfortable range for each of the body parts was covering up to 7 °C (for example, for the head the comfortable range was between 18 °C to 25 °C in the winter and between 20 °C to 26 °C in the summer), therefore the maximum 2 °C error introduced by the estimation method here appears to be low enough to deliver sufficient accuracy for HVAC control.

6 CONCLUSIONS

A multiple linear regression model that estimates equivalent temperature at several body parts of the occupant has been derived. When applying k-fold cross validation on trials in a controlled environment, equivalent temperature is predicted with average errors between 0.5 °C and 1.9 °C for various body parts while using only two sensors as input previously selected. On the trials in realistic driving scenarios errors between 1 °C and 2 °C were achieved. The equivalent temperature estimation method provides sufficient accuracy for controlling the HVAC system.

Since equivalent temperature integrates the effect of air flow, in future work we will examine the latter's impact on the estimation error and find optimal air flow sensor locations.

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