Mutual Information-based Sensor Positioning for Car Cabin Comfort Control

Diana Hintea[1], James Brusey[1], Elena Gaura[1], Neil Beloe[2], and David Bridge[3]

[1] Coventry University, Priory Lane, Coventry, CV1 5FB, UK
[2] Jaguar Land Rover Ltd, Abbey Road, Whitley, Coventry, CV3 4LF, UK
[3] MIRA Ltd, Watling Street, Nuneaton, CV10 0TU, UK

Abstract. Car cabins are transient, non-uniform thermal environments, both with respect to time and space. Identifying representative locations for the Heating, Ventilation and Air Conditioning (HVAC) system sensors is an open research problem. Common sensor positioning approaches are driven by considerations such as cost or aesthetics, which may impact on the performance/outputs of the HVAC system and thus occupants' comfort. Based on experimental data, this paper quantifies the spacial-temporal variations in the cabin's environment by using Mutual Information (MI) as a similarity measure. The overarching aim for the work is to find optimal (but practical) locations for sensors that: i) can produce accurate estimates of temperature at locations where sensors would be difficult to place, such as on an occupant's face or abdomen and ii) thus, support the development of *occupant* rather than *cabin* focused HVAC control algorithms. When applied to experimental data from stable and hot/cold soaking scenarios, the method proposed successfully identified practical sensor locations which estimate face and abdomen temperatures of an occupant with less than 0.7 ℃ and 0.5 ℃ error, respectively.

1 Introduction

The role of Heating, Ventilation and Air Conditioning (HVAC) in cars is to keep passengers comfortable or, more correctly, to avoid their discomfort. Traditionally, the HVAC energy budget has been generous. However, with the introduction of electric and hybrid electric vehicles, any additional energy usage by the HVAC system reduces the range, and thus, the usefulness of the car. Energy efficient approaches to control are called for, potentially based on local conditioning of occupied cabin areas and driven by occupants' perceptions of the environment rather than set-point temperatures.

Several novel approaches to HVAC control have been presented in the literature. Generally, such approaches are concerned with directly controlling the comfort of the cabin occupants. Comfort is estimated by applying a model, such as Predicted Mean Value (PMV) [3], to the cabin sensed data. The success of such control algorithms heavily relies on an accurate representation of the sensed phenomena at specific points, i.e in the immediate vicinity of the occupant, and also presume the cabin environment to be relatively stable.

A parallel line of work in the domain takes advantage of enhanced understanding of human physiology and proposes models for estimating the occupant's thermal sensation and, with it, thermal comfort. Thermal sensation can be predicted either for the whole body or for individual body parts and common model inputs are local skin temperature, mean skin temperature and core body temperature, together reflecting the overall thermal state of the body. The Berkeley Comfort Model [6] and Zhang's Model [14] are the best empirical models to date and are used by most advanced automotive simulators such as RadTherm [10] for evaluating cabin environments.

Whilst expected to deliver a more accurate representation of the comfort experienced by occupants, physiological comfort models can not be directly used for HVAC control as it is impractical to acquire the necessary inputs (i.e. skin temperature at various points). The inputs could, however, be estimated from suitable cabin data. The prerequisites are: i) a good understanding of the cabin environment and the relationships between various sensing locations within the cabin and ii) a method of estimating with sufficient accuracy human skin temperature in a variety of conditions, from cabin data.

The work here proposes a Mutual Information (MI) based method as an aid to understanding the cabin environment and the spacial relationships between temperatures within the cabin. MI quantifies the shared informational content between a source sensor location and a target virtual location (such as various occupant skin sites). Within an experimental set-up which makes available not only cabin data at multiple points, but also occupant skin temperature data, the method allows the selection of practical cabin sensor locations best suited for estimating skin temperatures.

The paper is structured as follows. Section 2 presents related work in the areas of HVAC control and sensor positioning. Section 3 describes the methods developed for calculating the MI between sensor locations within a car cabin environment. Section 4 presents the results obtained when applying the MI methods to experimental data and Section 5 concludes the paper.

2 Related Work

Numerous attempts exist in the literature towards developing comfort control algorithms. Torres *et al.* [13] designed and implemented a neural network based control algorithm, using a back-propagation learning method. Though good results were achieved based on a simple neural network, a disadvantage is represented by the network's long training duration. In order to make the learning process less time consuming, Luo *et al.* [7] worked on a Fuzzy Neural Network (FNN) model for predicting clothing thermal functions, based on body core and skin temperatures. Another fuzzy logic-based control algorithm was presented by Stephen *et al.* [12]. The method simplified and converted Fanger's [3] PMV equations into fuzzy rules. However, the results were simulation-based and the controller's effectiveness was not clear from the results.

The works described above assume that the sensor data driving the control algorithms is a perfect representation of the cabin environment. The complexity and dynamics of the cabin are not considered. Spacial-temporal thermal variations in the cabin are however significant, as observed experimentally by the authors here in a variety of controlled tests.

Although not specifically dealing with cabin environments, a number of works in the literature are concerned with strategies for finding optimal sensor locations in similar complex environments. Guestrin *et al.* [4] chose a MI criteria (a measure of the amount of shared information between two random variables [2,8]) and implemented a polynomial-time approximation for maximizing the MI, leading to better sensor placements. A Bayesian approach used for optimally locating a sensor with respect to the others was described by Cameron *et al.* [1]. In this method the expectations regarding the sensing environment were updated based on the acquired sensor data and the next sensor locations were chosen by taking into account this prior information. Shah *et al.* [11] dealt with the problem of optimally positioning sensors in lumped and distributed parameter dynamic systems. The covariance of the parameter estimates was computed and the sensor locations were found by minimizing the covariance matrix. Using the concept of entropy, Papadimitriou *et al.* [9] illustrated a method for optimally locating the sensors in a structure in order to extract from the measured data the most valuable information about the model's parameters. Another entropy-based sensor placement method was developed by Gutierrez *et al.* [5]. A maximum entropy approach for selecting the corresponding probability distributions was used with the purpose of minimizing the average detection error for fault locations.

A MI based approach has been adopted in this work and is further presented in the next section.

3 Mutual Information-based Method

The MI computation method described here is based on finding entropies, leading to a multivariate Gaussian assumption over the variables. The normal distribution hypothesis was confirmed by applying the D'Agostino normality test on the experimental data sets.

A series of methods were researched towards the purpose of computing the MI. The first belongs to the discrete case and consists of sampling the raw data, the second one derives an approximate continuous curve that matches the probability distribution observed in the raw data. A third method implemented belongs to the continuous case and it consists of a numerical approximation to the integral definition of MI. The method presented further on was selected over the above described methods since it gave results consistent with expectations for all experimental data.

The MI computation method contains the steps in Figure 1, described in what follows.

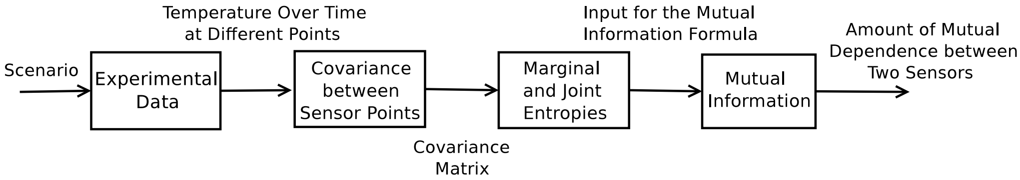

Fig. 1. Flow chart of the entropy-based approach of computing the mutual information

3.1 Gathering the Experimental Data

A series of experiments were performed in a climatic wind tunnel with a state of the art vehicle, as follows:

- Five 54 minutes long steady state experiments, each with three occupants in the car. The car cabin air temperature was initially set to 22 ℃, and increased by 1 ℃ per minute, towards a final temperature of 26 ℃. For the second part of the experiment, the temperature was gradually decreased to 16 ℃, and finally brought back to 22 ℃. The car was in idle state during the initial, middle and final parts of the experiment when the temperatures were maintained at 22 ℃, 16 ℃ and 22 ℃, respectively and driven at a constant speed of 50 km/h when the temperature increments were performed.
- Two warm-up experiments, each 70 minutes long. The car was initially soaked to -18 ℃. The experiments began by setting the cabin's thermostat to the highest possible temperature (first experiment), and 22 ℃, respectively (second experiment). There were two cabin occupants each time and the car was driven at a constant speed of 50 km/h for the first 30 minutes, and 100 km/h for the rest of each experiment.

The cabin and occupant sensor data was acquired with a frequency of 0.1Hz. The sensorized occupant was in the front passenger seat for all above experiments. 4 skin sensors were used: face, upper arm, chest and abdomen. The cabin had standard instrumentation consisting of a thermocouple harness with 32 sensors (locations shown in Figure 2). The abbreviations used in Figure 2 are: L = left, R = right, R1 = row containing the front seats, R2 = row containing the back seats, while the discharge sensors are the sensors placed at the air conditioning vent outlets.

In what follows, skin temperature is referred to as the *target variable* (or simply target). Similarly, the locations of sensors that can be practically considered for HVAC control are referred to as *source variables* (or sources).

3.2 Computing the Marginal Entropies and the Mutual Information

Given two sensors X and Y, let X be the target location and Y the source location. Using the entropy concept, the MI between the source and target can be expressed as:

$$I(X;Y) = H(X) - H(X \mid Y), \tag{1}$$

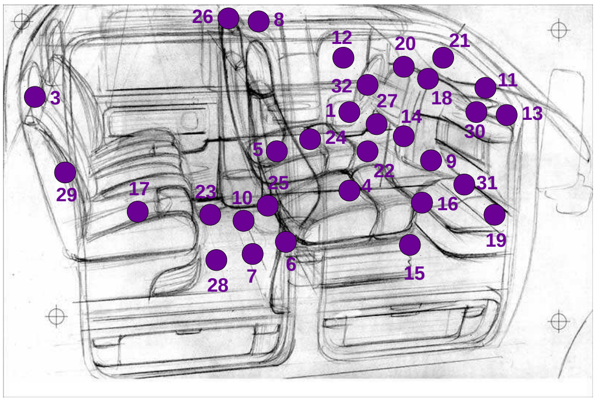

Fig. 2. Source sensor locations

where $H(X), H(Y)$ denote the marginal entropies of the two random variables and $H(X \mid Y)$ is the conditional entropy of X knowing Y.

Using the conditional entropy definition, MI can be written as:

$$I(X;Y) = H(X) - H(Y) + H(X,Y).$$

Both the marginal entropies $H(X), H(Y)$ and the joint entropy $H(X,Y)$ can be computed from the general joint entropy formula for a multivariate normal distribution:

$$H(X_1, X_2, ..., X_k) = \frac{1}{2} \ln \left((2\pi e)^k |\Sigma| \right), \tag{2}$$

where k represents the number of random variables forming the distribution and Σ is the covariance matrix of the variables.

3.3 Extending the Mutual Information Concept for Multiple Sources

In order to represent more accurately the point of interest, namely the target location, computing the MI from multiple source sensors is considered.

Given three sensors X, Y and Z, let X be the target location and Y and Z be the source locations. Based on equation 1, the MI between the two sources and the target can be written as:

$$I\left(X;Y,Z\right)=H\left(X\right)-H\left(X|Y,Z\right).$$

The conditional entropy can be written as following:

$$H(X|Y,Z)=H(X,Y,Z)-H(Y,Z),$$

where $H(X,Y,Z)$ is the joint entropy for the three sensors, while $H(Y,Z)$ is the joint entropy for the two sensor sources.

Finally, MI can be defined as:

$$I(X;Y,Z)=H(X)+H(Y,Z)-H(X,Y,Z)$$

The marginal entropy $H(X)$, as well as the multiple joint entropies ($H(Y,Z)$ and $H(X,Y,Z)$), can be computed using equation 2.

4 Evaluation of the Method on Experimental Data

4.1 Mutual Information Outcomes between a Source Sensor and a Target Sensor

The MI values between source sensors (32 cabin locations as per Figure 2) and two target locations (face and abdomen of the front row passenger) were calculated, over the whole experimental data bank. MI values for the FACE target varied between 0.0003 and 1.05, with the highest MI obtained from the "R2DischargeR" sensor. For the ABDOMEN target, the lowest MI value was 0.0001 and the highest 0.67, obtained from the "R2RSeatCushion" sensor. Table 1 shows a sample of source locations and their respective MI values for FACE and ABDOMEN targets. The table also presents results for the estimation accuracy which would be achieved by using the respective source - target pair. (This estimation method is presented elsewhere.)

For both target locations, as the MI values decrease, the estimation accuracy decreases too, as expected. However, no direct relationship was observed here between the MI value and the estimation accuracy across the two targets (Figure 3).

Figure 4 represents graphically the MI between pairs of target sensors and potential source sensors. The line thickness is directly proportional to the MI value.

4.2 Mutual Information Outcomes between Two Source Sensors and a Target Sensor

Table 2 illustrates how MI changes when two source sensors are considered jointly. The use of two source sensors resulted in higher MI values throughout the source and target pairs considered. The highest MI value for the FACE target was 1.19, obtained from the "R2DischargeR" and "R2FootR" combination of sensors. For the ABDOMEN target, the highest MI value was 0.76, obtained from the "DriverSeatCushion" and "PassengerSeatCushion" combination of sensors.

Target Sensor: Face		Temperature Estimation
Source Sensor	MI	RMSE(℃)(mean±std)
R2DischargeR	1.05	0.7±0.08
HeadlinerIntRearPassHead	0.86	0.86±0.09
SteeringWheel	0.67	1.05±0.1
R2FootR	0.64	1.06±0.16
IPTopRCentre	0.48	1.2±0.09
R1DischargeInnerL	0.37	1.4±0.14
FrontSideGlassLCentre	0.09	1.9±0.2
Target Sensor: Abdomen		Temperature Estimation
Source Sensor	MI	RMSE(℃)(mean±std)
R2RSeatCushion	0.67	0.52±0.06
IPTopRCentre	0.61	0.55±0.06
PassengerSeatBack	0.59	0.56±0.06
PassengerSeatCushion	0.56	0.58±0.05
PanoramicDriverHead	0.36	0.72±0.06
FrontSideGlassRCentre	0.27	0.8±0.03
R1FootR	0.05	1.0±0.02

Table 1. MI results for face and abdomen selected as target sensors

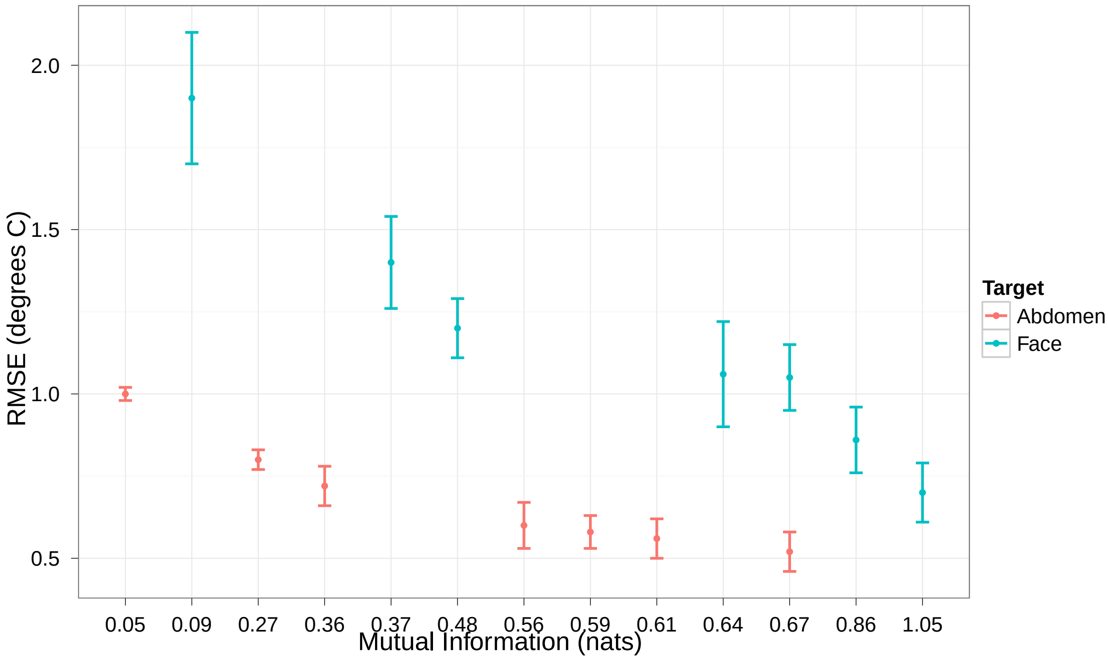

Fig. 3. MI values and their corresponding estimation accuracy

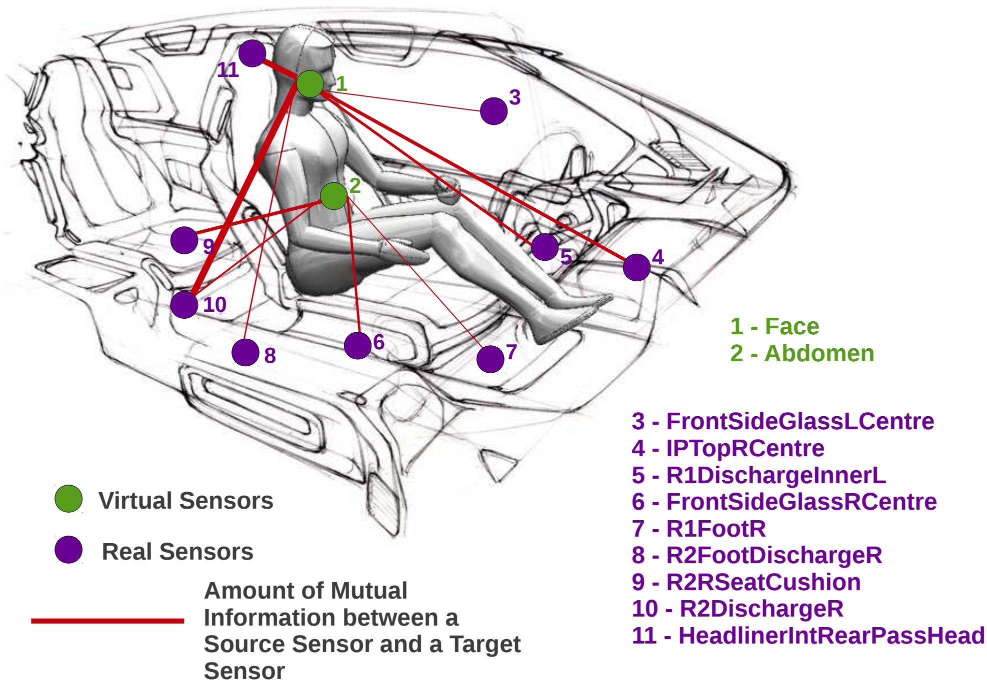

Fig. 4. MI relations between the two target sensors and some of the source sensors

Target Sensor: Face			Temperature Estimation
Source Sensor 1	Source Sensor 2	MI	RMSE(°C)(mean±std)
R2DischargeR	R2FootR	1.19	0.62±0.10
R2DischargeR	HeadlinerIntRearPassHead	1.17	0.64±0.08
R2DischargeR	R2FootL	1.16	0.66±0.09
PassengerSeatCushion	HeadlinerIntRearPassHead	1.15	0.66±0.09
R2DischargeR	R1FootL	1.14	0.66±0.09

Target Sensor: Abdomen			Temperature Estimation
Source Sensor 1	Source Sensor 2	MI	RMSE(°C)(mean±std)
DriverSeatCushion	PassengerSeatCushion	0.756	0.49±0.04
R2RSeatCushion	IPTopRCentre	0.683	0.524±0.06
R2RSeatCushion	PassengerSeatCushion	0.683	0.526±0.06
R1DischargeOuterR	R1FootL	0.682	0.527±0.04
R2FootR	R2RSeatCushion	0.679	0.526±0.06

Table 2. Best five MI scores for face and abdomen selected as target sensors

5 Conclusions and Further Work

The work described a method of identifying optimal sensor locations for estimating temperature at defined target locations, such as the face or abdomen of a cabin's occupant. A first step towards this aim was to establish a robust method for accurately quantifying how closely related various sensor data streams are. The Mutual Information between sensors was found to be an appropriate measure for the application at hand.

For the face selected as target location, the "R2DischargeR" source sensor delivered the highest MI value, leading to an estimation accuracy of 0.7 ℃. For the abdomen selected as target location, an estimation accuracy of 0.52 ℃ was obtained with "R2RSeatCushion" as a source sensor. The method was extended to multiple sources in order to find combinations of sensors which lead to a better estimation of the target sensor. The estimation accuracy was further improved to 0.62 ℃ for the face as target with "R2DischargeR" and "R2FootR" as source sensors. For the abdomen as target, the estimation accuracy was increased to 0.49 ℃ with "DriverSeatCushion" and "PassengerSeatCushion" as source sensors.

With regard to future work, it is planned to estimate the overall comfort of all occupants within a car cabin. Several source and target locations will be used with the purpose of maximizing the MI among them. It is also planned to implement a reinforcement learning HVAC algorithm used to train the system to adjust set-points. Embedding this algorithm into the car's HVAC system implies that the HVAC control will gradually learn user's preferences with the purpose of reducing the instances of user intervention whilst maintaining the occupants' comfort and reducing the energy consumption.

Acknowledgements

The Low Carbon Vehicle Technology Project (LCVTP) is a collaborative research project between leading automotive companies and research partners, revolutionising the way vehicles are powered and manufactured. The project partners include Jaguar Land Rover, Tata Motors European Technical Centre, Ricardo, MIRA LTD., Zytek, WMG and Coventry University. The project includes 15 automotive technology development work-streams that will deliver technological and socio-economic outputs that will benefit the West Midlands Region. The £19 million project is funded by Advantage West Midlands (AWM) and the European Regional Development Fund (ERDF).

References

1. Alec Cameron and Hugh Durrant-Whyte. A bayesian approach to optimal sensor placement. *The International Journal of Robotics Research*, 9, 1990.
2. Thomas M. Cover and Joy A. Thomas. *Elements of Information Theory*. John Wiley & Sons, Inc., 1991.

3. P.O. Fanger. *Thermal Comfort*. PhD thesis, Technical University of Denmark, 1970.
4. Carlos Guestrin, Andreas Krause, and Ajit Paul Singh. Near-optimal sensor placements in gaussian processes. In *ICML '05 Proceedings of the 22nd international conference on Machine learning*, 2005.
5. J. M. Gutierrez, V. Kreinovich, R. Osegueda, C. Ferregut, and M. J. George. Maximum entropy approach to optimal sensor placement for aerospace non-destructive testing. In *Maximum Entropy and Bayesian Methods*, 1998.
6. C. Huizenga, H. Zhang, T. Duan, and E. Arens. An improved multinode model of human physiology and thermal comfort. In *Building Simulation*, 1999.
7. Xiaonan Luo, Wenbang Hou, Yi Li, and Zhong Wang. A fuzzy neural network model for predicting clothing thermal comfort. *Computers & Mathematics with Applications*, 53:pp. 1840-1846, 2007.
8. Liam Paninski. Estimation of entropy and mutual information. *Neural Computation*, 15:pp. 1191-1253, 2003.
9. Costas Papadimitriou, James L.Beck, and Siu-Kui Au. Entropy-based optimal sensor location for structural model updating. *Journal of Vibration and Control*, 6:pp. 781-802, 2000.
10. RadTherm©. ThermoAnalytics Inc., Heat Transfer Analysis Software. http://www.thermoanalytics.com/products/radtherm/index.html; Accessed on the 6th of April 2011.
11. P. C. Shah and F. E. Udwadia. A methodology for optimal sensor locations for identification of dynamic systems. *Journal of Applied Mechanics*, 45:pp. 188-197, 1978.
12. Elizabeth Amudhini Stephen, Mercy Shnathi, P. Rajalakshmy, and M. Melbern Parthido. Application of fuzzy logic in control of thermal comfort. *International Journal of Computational and Applied Mathematics*, 5:pp.289-300, 2010.
13. Jose Luis Torres and Marcelo Luis Martin. Adaptive control of thermal comfort using neural networks. *Argentine Symposium on Computing Technology*, 2008.
14. H. Zhang. *Human Thermal Sensation and Comfort in Transient and Non-Uniform Thermal Environments.* PhD thesis, University of California, Berkeley, 2003.