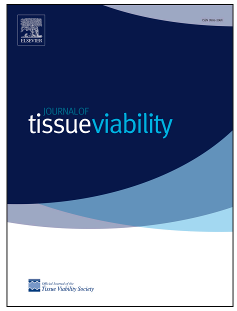
http://dx.doi.org/10.1016/j.jtv.2015.08.001

Liu, Z., Wang, L., Luo, Z., Heusch, A.I., Cascioli, V. and McCarthy, P.W. (2015)
Microenvironment temperature prediction between body and seat interface using autoregressive data-driven model.
Journal of Tissue Viability, 24 (4). pp. 131-139.

Accepted Manuscript



Microenvironment temperature prediction between body and seat interface using autoregressive data-driven model

Zhuofu Liu, Lin Wang, Zhongming Luo, Andrew I. Heusch, Vincenzo Cascioli, Peter W. McCarthy

PII: S0965-206X(15)00071-6

DOI: 10.1016/j.jtv.2015.08.001

Reference: JTV 174

To appear in: *Journal of Tissue Viability*

Received Date: 23 May 2015

Revised Date: 4 July 2015

Accepted Date: 10 August 2015

Please cite this article as: Liu Z, Wang L, Luo Z, Heusch AI, Cascioli V, McCarthy PW, Microenvironment temperature prediction between body and seat interface using autoregressive data-driven model, *Journal of Tissue Viability* (2015), doi: 10.1016/j.jtv.2015.08.001.

Microenvironment temperature prediction between body and seat interface using autoregressive data-driven model

Zhuofu Liu[1*], Lin Wang[1], Zhongming Luo[1], Andrew I Heusch[2], Vincenzo Cascioli[3], Peter W McCarthy [2]

[1] The higher educational key laboratory for Measuring & Control Technology and Instrumentations of Heilongjiang Province, Harbin University of Science and Technology, Harbin, Heilongjiang, 150040, China, Zhuofu_liu@hrbust.edu.cn

[2] Welsh Institute of Chiropractic, University of South Wales, Treforest, Pontypridd, CF37 1DL, United Kingdom

[3] Murdoch University Chiropractic Clinic, Murdoch, 6150, Western Australia

*Corresponding author's email: zhuofu_liu@hrbust.edu.cn

Abstract

There is a need to develop a greater understanding of temperature at the skin-seat interface during prolonged seating from the perspectives of both industrial design (comfort/discomfort) and medical care (skin ulcer formation). Here we test the concept of predicting temperature at the seat surface and skin interface during prolonged sitting (such as required from wheelchair users). As caregivers are usually busy, such a method would give them warning ahead of a problem. This paper describes a data-driven model capable of predicting thermal changes and thus having the potential to provide an early warning (15- to 25-minute ahead prediction) of an impending temperature that may increase the risk for potential skin damages for those subject to enforced sitting and who have little or no sensory feedback from this area.

Initially, the oscillations of the original signal are suppressed using the reconstruction strategy of empirical mode decomposition (EMD). Consequentially, the autoregressive data-driven model can be used to predict future thermal trends based on a shorter period of acquisition, which reduces the possibility of introducing human errors and artefacts associated with longer duration "enforced" sitting by volunteers. In this study, the method had a maximum predictive error of <0.4 ^{o}C when used to predict the temperature at the seat and skin interface 15 minutes ahead, but required 45 minutes data prior to give this accuracy. Although the 45 minutes front loading of data appears large (in proportion to the 15 minute prediction), a relative strength derives from the fact that the same algorithm could be used on the other 4 sitting datasets created by the same individual, suggesting that the period of 45 minutes required to train the algorithm is transferable to other data from the same individual. This approach might be developed (along with incorporation of other measures such as movement and humidity) into a system that can give caregivers prior warning to help avoid exacerbating the skin disorders of patients who suffer from low body insensitivity and disability requiring them to be immobile in seats for prolonged periods.

Keywords: temperature prediction; prolonged sitting; EMD filter; autoregressive data-driven model

1. Introduction

Research interest in seat design and comfort evaluation has seen continued growth owing to the considerable amount of time being spent on sitting, both at home and in the office [1]. Nowhere is this more important than in relation to those people who have lost access to their natural feedback mechanisms which would warn them of impending skin damage due to hypoxia (compressed blood flow), hyper-humidity and high temperature. Currently, however there seems to be little consistency in the methodologies employed to investigate this area. Most research effort appears to be spent on design of the seat rather than on developing an understanding of the physiological issues related to patients with sensory deficits or using sensor-based systems as a replacement for neurological deficit. Hampering this further, the relationship between objectively measured parameters and the qualitative domain of comfort/discomfort are still unclear.

It is obvious that the thermal properties (heat absorption and dissipation) of a cushion can play a vital role in the evaluation of sitting comfort [1-4]. However, thermal characteristics might also have a bearing on tissue viability and as a consequence the likelihood of skin ulcer formation [5]. Interestingly, the effect of increased temperature due to sitting does not just affect skin viability; lesser changes in temperature can also cause more subtle changes. What might otherwise be considered as insignificant changes in temperature might contribute to the decrease in both semen quality and quantity; indeed increases in scrotal temperature of up to 3^{o}C have been reported following a 20-minute period of sitting on commonly used chairs [6], however those with spinal cord injury in wheelchairs tend to have higher scrotal temperatures than the non-spinal cord injured [7]. When scrotal skin temperature increases and normal thermoregulation mechanism is impaired, the local increase in temperature negatively impacts on semen quality (sperm concentration, motility and morphology) as well as sperm chromatin structure. From this perspective, it is important to recognise the need to limit the temperature change at the seat-skin interface during prolonged periods of sitting. This paper aimed to determine whether it was possible to derive a method which can offer advanced warnings of temperature change reaching an undesired level; changes which if left unaddressed might put the immobile person at risk of skin or other tissue damage.

According to the authors' knowledge [8, 9], direct assessment of the thermal properties between the body and seat interface has been subjected to little objective experimentation. Other approaches have included a focus on the more subjective domain, using indirect assessment of thermal comfort [10, 11]. The direct measurement approach has employed either infrared imaging [8], or direct measurement at the site [9]. Ferrarin and Ludwig [8] compared thermal transients of four seat materials at three test points (ischial and thighs). However, measurement was intermittent, as the subjects were required to stand up for 30 seconds every 5 minutes in order to image the seat by thermography, thus potentially adding an inconsistency to the temperature profile and increasing uncertainty that the subjects sat in a natural manner. Cengiz and Babilik [9], on the other hand, evaluated thermal change effects on comfort by placing eight measurement devices (under thigh, inner thigh, stomach, side of body, chest, waist, back, right bottom) on the skin of subjects who attended road trials of automobile seats and assessed seat comfort by questionnaires. Although mean temperatures were employed to compare thermal properties of three different seat covers, no sensors were placed at the body-seat interface to assess temperature at this site during the period of sitting.

The use of sensor systems with or without modelling to predict temperature change in order to limit damage or maintain comfort is not novel. Local skin (microenvironment) temperature has been used to predict core temperature variations based on mathematical modelling techniques, as telemetry methods suffer from instability (signal could not be detected) and self-generated noise (causing data artefacts) when used in more extreme environments [12]. A multi-linear regression model has been applied to predict local skin temperatures based on the measurement of 12 body locations (e.g. forehead, upper arms, hands and shins) in the study of airplane cabin temperature control [13]. However, in this study all information was acquired by infrared sensors, which were incapable measuring between body and seat surface.

The above synopsis illustrates some of the limitations previously faced when attempting to perform seat temperature experiments. From the perspective of subjects, the volunteers are requested to sit "normally" for prolonged periods. The stability of both sensors and data recording systems is critical to the success and therefore, also imposes challenges. However, it is important to develop a methodology which will allow generation of accurate and reproducible data from subjects who would sit in a manner as natural as possible, preferably unaware of the experimental data collection. Regardless of these factors, if it was possible to reduce the period of sitting required for gathering sufficient data (i.e. by use of a predictive system), this might allow development of clinically useful systems for sensory deprived people, or caregivers of neurologically compromised people; to warn of potentially damaging temperatures at this interface. Additionally, it might also open the door on the development of systems to predict comfort levels for customers in commercial outlets.

In the previous studies [14, 15], we have reported results from an objective seat measurement system developed to allow reliable recordings of temperature from 3 areas (thighs and the coccyx) at or close to the skin-seat interface microenvironment, using a low profile sensor based solution, without the need to disturbing the seated subjects. In this paper, we report the development of a data-driven model capable of predicting temperature changes based on experimental sitting data. The accuracy of the model was tested on data obtained from sitting experiments using the multi-channel body-seat interface temperature measurement system described previously [14].

2. Methodology

2.1. Experiments

All selected volunteers were healthy university students (four male and three female) with ages ranging from 19 to 23 years old. Based on the experimental requirements, healthy was defined as not suffering any condition that might lead to or include an increased core temperature such as a known current viral or bacterial infection and or thermoregulatory disorder [12, 13]. The BMI (body mass index) of all participants ranged from 19.38 to 24.57 kg/m^2.

Based on our previous studies [14, 15], three temperature sensors (LM35 National Semiconductor Corporation, USA), deemed most appropriate for temperature assessment on the seating surface, were placed approximately under each of the following relative positions: left mid-thigh, right mid-thigh and coccyx. As body temperatures would not be expected to vary abruptly over short periods (< 5 seconds) [14], the sampling frequency of the data acquisition system (Pico ADC-11/12, Pico Technology, UK) was set at 1Hz/sensor. The temperature sensors were calibrated before starting the experiments in the environment-controlled chamber of UKAS Accredited Calibration Laboratory under National Standard (Certificate of Calibration No. 0034). All acquired data were stored on the computer's hard drive in real time using a laboratory-developed application program [14]. Off-line signal processing and data analysis techniques were employed with the help of the Matlab software package (MathWorks USA).

Before taking part in the experiments, volunteers were asked to read an information sheet detailing the experimental protocol with their specific requirements and sign a consent form. Ethical approval was granted by the School of Applied Sciences Ethics Committee at the University of Glamorgan (now University of South Wales). The experimental protocol comprised each subject sitting for one hour on the commercially available foam cushion embedded with three temperature sensors. The cushion was mounted in a standard wheelchair. As a requirement, participants were asked not to undertake any vigorous physical exercise in the 24 hours prior to the experiment and were requested to only volunteer if they were not in a hurry to leave or had other calls on their time (e.g., coursework deadlines). Once in the laboratory, the volunteers were allowed to acclimatize to the environment for at least 15 minutes prior to taking part in the experiment: as recommended by previous studies [14, 15].

All volunteers were asked to attend the lab on five separate occasions (different days at their convenience, but at the same time of day in order to negate any diurnal differences) to repeat the same experiment (all experimental data were acquired from the beginning of December 2013 to the beginning of January 2014). During the experimental recording periods, volunteers were provided with books or music. All subjects completed their 1 hour of sitting in an upright sitting position without getting up (e.g. toilet), engaging in any large or excessive movements, or adopting any unusual postures (e.g. crossing their legs). Prior to each data collection, the initial surface temperature of the foam cushion was measured to ensure that all data could be referenced to the same start level (Mean ± SD: 27.1 ± 0.2 ^{o}C). The ambient temperature and relative humidity of the research room were monitored throughout the experimental period (temperature: 26.1±0.5 °C and relative humidity: 44%±3%) and air movement was minimal.

All volunteers were asked to wear cotton material trousers in order to reduce the impact of varying the clothing materials on relative insulation (degree of thermal insulation) or water vapour transfer (cooling) from the interface between body and seat.

2.2. EMD filter-based pre-processing

To reduce data artefacts and suppress unwanted noise, a data-driven filter, based on the EMD (Empirical Mode Decomposition) algorithm, was applied to the temperature data before carrying out further analysis. The procedure of EMD was proposed by Huang [16] with the kernel aim of sifting the original input signal until the final residual is stationary. The innovative part of the EMD method is the introduction of the IMF (Intrinsic Mode Function) components, which are based on the local natural properties of the signal and adaptively represent a non-stationary signal as a sum of zero-mean fast and slow oscillating modes.

The EMD method has been successfully used in various fields [17-20] such as engineering mechanics, biomedical engineering and mechanical failure detection. For an arbitrary data series, the sifting process is [16-18]:

(1) Extract all of the maxima and minima of the series $X(t)$

(2) Calculate the upper envelope $u(t)$ and the lower envelope $v(t)$ with cubic spline function. The mean envelope $m(t)$ is

$$m(t) = [u(t) + v(t)]/2 \tag{1}$$

(3) A new series with the low frequency removed is calculated by subtracting the mean envelope from the series

$$h_1(t) = X(t) - m(t) \tag{2}$$

Generally speaking, $h_1(t)$ is still a non-stationary series, so the above procedure must be repeated k times until the mean envelope is approximated to zero:

$$m_{k-1}(t) = [u_{k-1}(t) + v_{k-1}(t)]/2 \tag{3}$$

$$h_k(t) = h_{k-1}(t) - m_{k-1}(t) \tag{4}$$

(4) Then, the first IMF component from the data $c_1(t)$, and its residue $r_1(t)$ are designated as:

$$c_1(t) = h_k(t) \tag{5}$$

$$r_1(t) = X(t) - c_1(t) \tag{6}$$

In general, $c_1(t)$ represents the highest frequency component of the original series. Since the residue $r_1(t)$, still contains information of longer period components, it is treated as the new data series and subjected to a new sifting process. The procedure is repeated for all subsequent residues until $r_n(t)$ is less than the pre-set threshold value or a monotonic function.

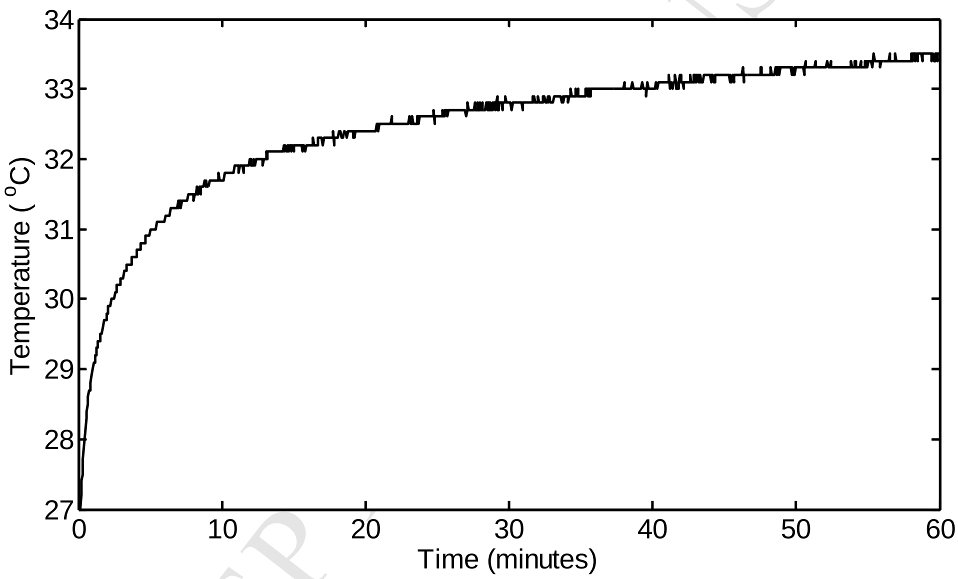


Figure 1 Data of the one-hour seating experiment contains fluctuating noise.

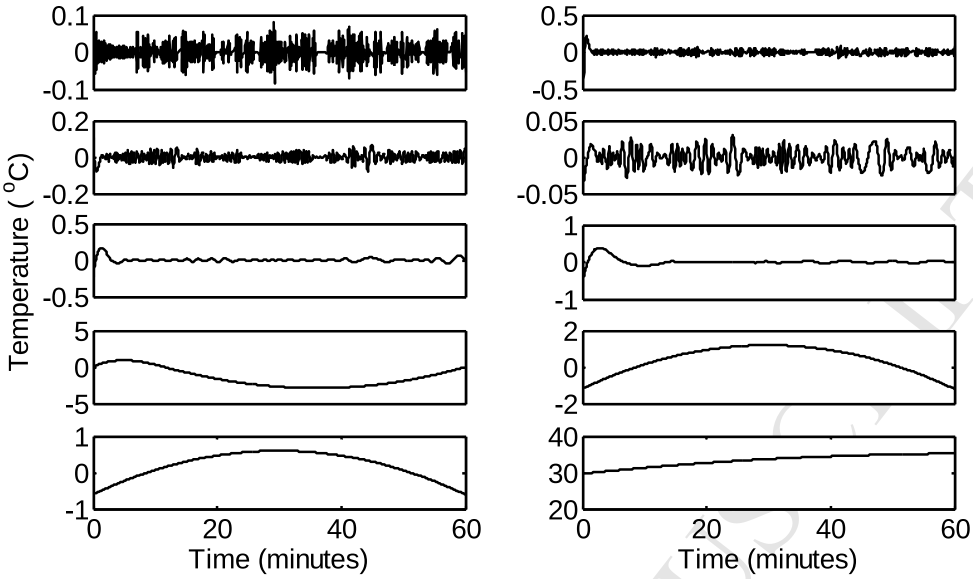


Figure 2 Demonstration of empirical mode decomposition (EMD) for the body-seat interface temperature data. The first IMF component (IMF1) is on the top left, followed by the second IMF component (IMF2) on the top right, and then IMF3 to IMF9 from left to right and top to bottom. The last subplot is the residue of the EMD procedure shown on the bottom right.

The original data from one subject who sat on a foam cushion for one hour contained a fast oscillating noise (Figure 1). Therefore, the aim is to remove the fluctuation while maintaining the veracity of the slowly varying trend in the recording. To accomplish this, the contaminated signal was decomposed into some standardized IMF components as well as one residual signal with the help of the EMD method (Figure 2). To determine which part of the decomposed components is useful, it is necessary to analyse the EMD outcomes theoretically.

Both Wu [18] and Molla [19] have illustrated that IMF components still belong to a normal distribution and that the mathematical expectations of IMFs dominated by noise are nearly zero. Based on this assumption, we removed unwanted fluctuating noise by setting a zero-crossing number as the threshold and reconstructed the noise-free signal using the decomposed parts that had a zero-crossing number smaller than the threshold. As mentioned in our previous work [20], the IMF5 to IMF9 and the residue presented in Figure 2 have slow oscillations and should be retained as the meaningful information. Conversely, IMF1 to IMF4 should be removed since they have larger zero-crossing numbers which mean higher frequency. Using the inverse EMD procedure, the filtered signal can be reconstructed (Figure 3).

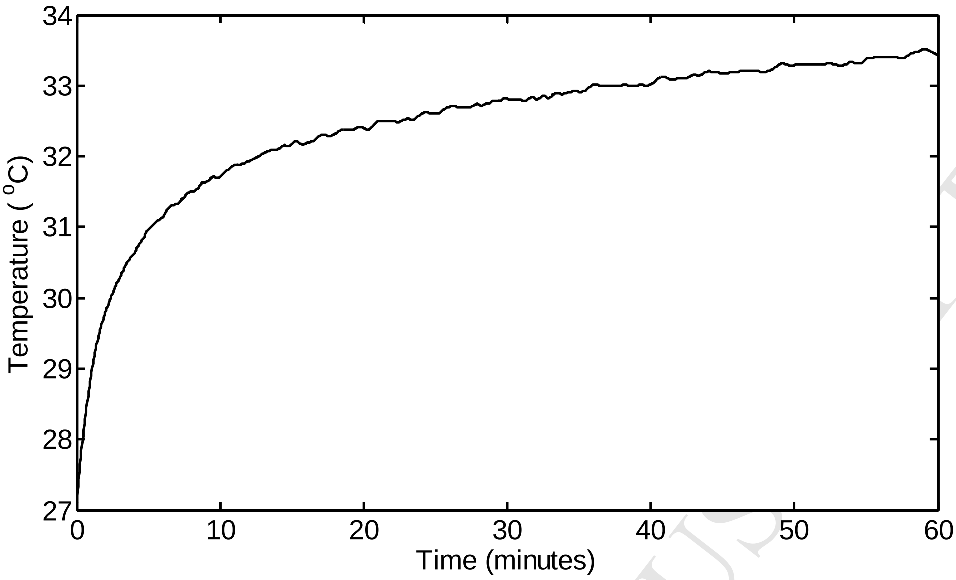


Figure 3 Noise-free signal created using the EMD reconstruction method. From this, it is apparent that the curve becomes almost plateaued after 45 minutes. This shape suggests accurate predicting of temperature trends should be possible. The advantage of temperature prediction would be to provide information for people with impaired sensation who might be restricted to periods of prolonged sedentary / seated activities (e.g. wheel-chair bound disabilities) or their caregivers: with the purpose of preventing ulcer formation or other forms of skin tissue damages due to prolonged sitting.

2.3. Autoregressive prediction model

In the temperature prediction process, the autoregressive (AR) model [12], one of the most widely used data-driven models, is employed as a function for future data estimation using previous observations. The AR model is

$$\hat{x}_n = \sum_{i=1}^{m} \varphi_i x_{n-i} + \varepsilon_n \tag{7}$$

where φ refers to the vector of AR parameters to be calculated, ε_n represents white noise and m denotes the order of the model. There are many ways to estimate the AR model parameters. In our application, the least square method was used to solve the parameter vector φ.

To compare the prediction performance of temperature based on the AR model, the root mean square error (RMSE) was employed and defined as:

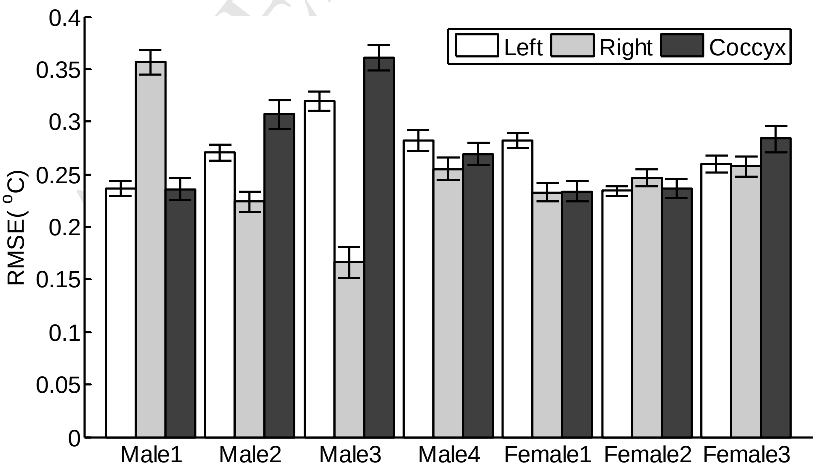
$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2}{N}} \tag{8}$$

where y_i is the i^{th} observed response value, $\hat{y}_i$ is the i^{th} predicted response value and N is the number of data points.

3. Results and discussions

Before carrying out any further analysis, a Kolmogorov-Smirnov test was initially used to determine normality of the data. After that, two types of temperature (as recorded at the skin surface-seat interface) predicting trials were performed using data from one hour sitting. Predictions made from sections of the data (the first 45 minutes, 40 minutes or 35 minutes) were compared to the measured data in order to test the accuracy of the prediction model.

Data Analysis I (Temperature prediction within the same experiment for each participant): the purpose of this experiment was to investigate if the data-driven model, trained on part of the data for a given experiment, could predict other parts of the data from the same experiment that had not been used for training. To test this hypothesis, data from the first 45 minutes (prediction over the final 15 minutes), 40 minutes (prediction over the final 20 minutes) or 35 minutes (prediction over the final 25 minutes) for each subject were selected as training data, while the remaining part belonging to the same experimental data set was used as testing data to verify the experiment-specified AR data-driven models. As a result, 15 different models for each subject (5×3, five repeated experiments for each participant at each of the three measurement positions) were developed respectively for each prediction (15-minute, 20-minute and 25-minute prediction). Then each model was applied to the data in order to predict the body-seat interface temperature for the corresponding experiment of each individual. The averaged RMSE values for each experiment-specified model are presented in Figure 4 along with the standard deviation functioning as an indication of the error.



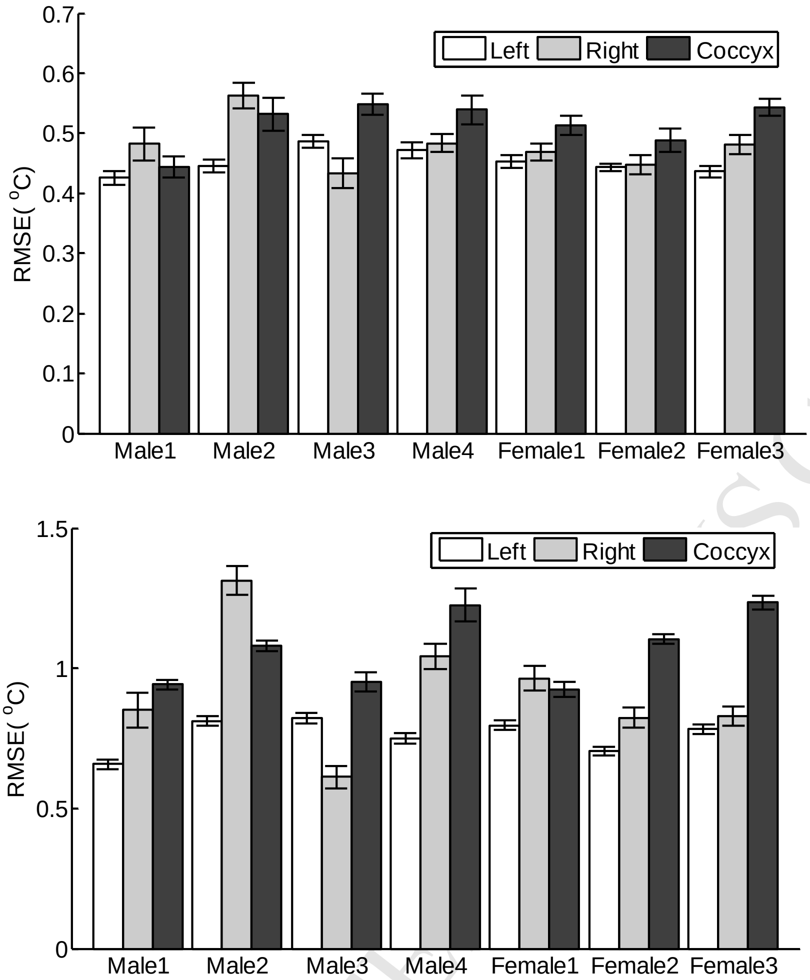


Figure 4 Results of Data Analysis I: RMSE of body-seat interface temperature prediction for the same experiment of each participant. The error bounds correspond to the standard deviation which is calculated over the five experiments. Top (a): 15-minute prediction using the first 45 minutes data, Middle (b): 20-minute prediction based on the first 40 minutes data, and Bottom (c): 25-minute prediction by the first 35 minutes data.

The results appear promising, indicating that the AR data-driven model can perform well if each model is applied to predict data outcomes from the same experiments for the same participant under similar environmental conditions (e.g. room temperature and relative humidity). As expected, the predictive capability of the model relies highly on the amounts of training data: i.e., the larger the training data pool, the smaller the prediction error (RMSE). The maximum averaged RMSE values for the 15-minute, 20-minute and 25-minute predictions were 0.36±0.02 ^{o}C, 0.56±0.03 ^{o}C and 1.31±0.05 ^{o}C (Mean ± SD, respectively). Practically, the use of an alarm system based on a 15-minute prediction should be sufficient to allow a susceptible, immobile people adequate time to take appropriate intervention measures (e.g. call for help, use their upper body to lift their buttocks away for the seat interface, or move their legs to allow circulation of air) to prevent prolonged seat-related skin problems developing. As the maximum deviation

(Mean + SD) of five repeated experiments for the 15-minute prediction shows the averaged RMSE to be < 0.4 ^{o}C, the AR data-driven model appears to have the ability to offer an acceptable prediction accuracy.

An ANOVA statistical analysis was employed to compare prediction values generated by the AR data-driven model in order to study if any relationship existed among the three models developed by the data from each of the different sensor locations (Left mid-thigh, Right mid-thigh and Coccyx). The output from the ANOVA revealed a significant difference ($p<<0.01$) between the data from each of the three positions, which once more attests to the individuality of the three sensor positions; as outlined in our pilot study [15].

Data Analysis II (Temperature prediction for cross experiments of each participant): the aim was to determine the intra-reliability of the method: for instance can the model developed using an element of one individual's data sets be applied to other data belonging to the same individual, but acquired at different times? One of the five experiments (randomly selected) for each participant (3 males and 4 females) was used to build up the prediction model, while the other four data sets for each of the same participants were used as test data.

Since the 15-minute prediction is capable of meeting our demands, *vide supra*, model development followed the procedure described above using the first 45 minutes of data. As a result, seven different models were developed with each model representing a specific participant. The prediction error values (averaged RMSE) for each participant-specified model are presented in Figure 5, along with the standard deviation to illustrate error boundaries. It is interesting to note that the prediction satisfied the requirements regarding accuracy (max deviation is 0.47±0.06 ^{o}C), even though the RMSE values were slightly larger than those of the self-generated models (Figure 4(a)). The sources of deviation may be attributed to various factors many of which are physiological and psychological. Although attempts had been made to compensate for diurnal changes, by making the measurements at similar times of day, numerous factors such as degree of sweating, changes of the metabolic rate (recent food intake and exercise), relative differences in mood which could have affected the volunteer's perception of the experiment, will tend to vary across the repeated experiments. As movement (amount and type) probably forms part of the normal persons reaction to their perception of the comfort of this environment, it is anticipated that the stability of the model will increase when tested on wheelchair users who do not have this facility available.

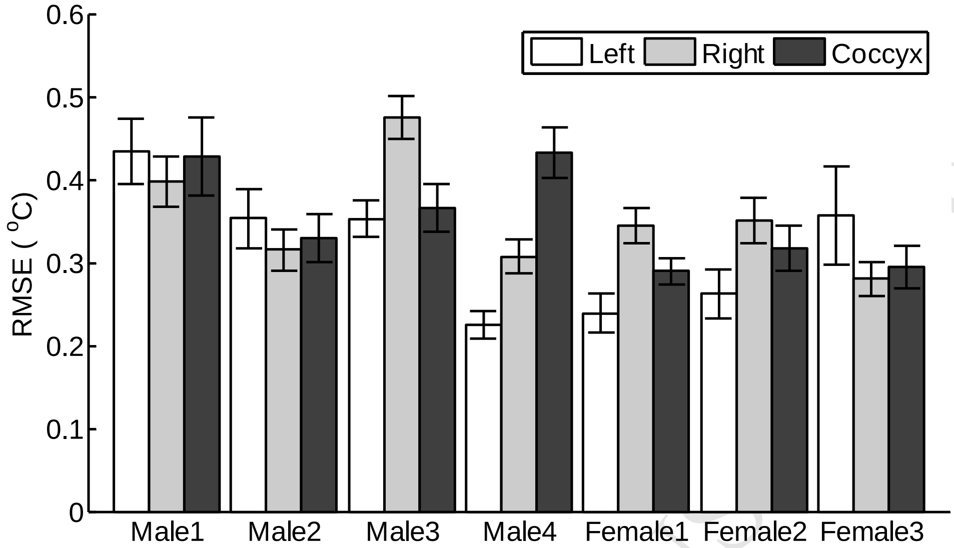


Figure 5 Results of Data Analysis II: RMSE of body-seat interface temperature prediction for cross experiments of each participant. The error bounds correspond to the standard deviation which is calculated over the other four experiments used as the testing group.

Though the majority of previous studies [21, 22] have paid more attention to the study of pressure distribution between the body-seat interface, Gefen [23] proposed a mathematical model that includes the connection between the skin temperature and pressure ulcers while suggesting possible interventions to reduce potential risks by optimizing microclimate factors (e.g. temperature and relative humidity). Even though some guidelines were reported in order to minimise the development of pressure ulcers, to the authors' knowledge, few applicable risk prevention tools have been developed to date [24, 25]. As temperature increases so does metabolism. Normally perfused skin reacts by increasing blood flow, however in compressed skin (such as that at the interface between person and seat surface) blood flow is being compromised and the conditions are generally considered to be ischemic. Therefore, the determination of what is a critical temperature in these conditions must take into account skin viability and duration of sitting as well as temperature. As yet this work has not been performed, however this study gives an opportunity to start the process by both accurately measuring temperature at the region and having the capacity to generate a warning in advance. Once consensus has been reached in relation to conditions identified above, then a critical temperature can be more sensibly determined. If temperature at this interface were to be recognised for its potential clinical importance at present, in order for a clinician or caregiver to measure the skin temperature, there would need to be either access made for the probe (movement which would defeat the purpose and cost clinician time). Alternatively, a temperature sensor could be set in place already; however, this would have a display for the output that would require constant awareness by the clinical team. Our suggestion could be used to create an alarm system which not only indicates that a critical limit has been reached, but also allows time for the caregiver/clinical team to perform the required function, rather than create an emergency situation (which is what would happen if a simple number was displayed). Based upon the predictive results proposed in this paper, 15 minutes warning of an impending critical temperature should be a sufficient amount of time for appropriate action to be taken at leisure whether by the person or their caregiver.

4. Conclusions

This study has shown the AR data-driven model to be capable of reliably predicting temperature trends at the body-seat interface microenvironment 15 minutes ahead of time. The maximum deviation between the prediction value and the corresponding measurement is < 0.4 ^{o}C when using data from the first 45 minutes of the one hour data sets. Results of the cross evaluation for the same subject (the model developed from any of the five experiments for a participant then applied to each of the other four experiments) showed that the AR data-driven model has a good general applicability for use within the same normal individual (maximum deviation from 0.41 ^{o}C to 0.53 ^{o}C for the 15-minute prediction).

The potential uses of the introduced methodology include: 1) development of an alarm mechanism to provide a warning temperature in advance of reaching a potentially damaging temperature, for example, local exacerbation of skin disorders, or increased risk of thermal acceleration of skin ischaemic damage or potential temperature based scrotal viability issues in males (malfunction of scrotal thermoregulation can lead to male infertility and semen deterioration) and 2) an attempt to facilitate recognition and study of other factors involved in ulcer formation; 3) an easier means to analyse the thermal properties of different seating materials while in use.

It is possible that the predictive methodology could be refined to decrease the data capture time yet increase the period of prediction. However, it is anticipated that a wider data collection to include environmental parameters (such as room temperature and relative humidity), BMI (body mass index), body fat, age and other aspects relevant to clothing and cushion materials will be required to do this.

5. References

[1] Huizenga C, Hui Z, Arens E. A model of human physiology and comfort for assessing complex thermal environments. Building and Environment 2001; 36:691-699.

[2] Munir A, Takada S, Matsushita T. Re-evaluation of Stolwijk's 25-node human thermal model under thermal-transient conditions: prediction of skin temperature in low-activity conditions. Building and Environment 2009; 44:1777-1787.

[3] Schweiker M, Shukuya M. Adaptive comfort from the viewpoint of human body energy consumption. Building and Environment 2012;51:351-360.

[4] Watanabe S, Shimomura T, Miyazaki H. Thermal evaluation of a chair with fans as an individually controlled system. Building and Environment, 2009; 44(7): 1392-1398.

[5] Andersen ES Karlsmark T. Evaluation of four non-invasive methods for examination and characterization of pressure ulcers. Skin Research and Technology 2008; 14: 270–76.

[6] Koskelo R, Zaproudina N, Vuorikari K. High scrotal temperatures and chairs in the pathophysiology of poor semen quality. Pathophysiology 2005; (11) 4: 221-224

[7] Jurewicz J, Radwan M, Sobala W, et.al. Effects of occupational exposure - is there a link between exposure based on an occupational questionnaire and semen quality? Systems Biology in Reproductive Medicine 2014; 60(4):227-233.

[8] Ferrarin M., Ludwig N. Analysis of thermal properties of wheelchair cushions with thermography. Medical and Biological Engineering and Computing. 2000; 38: 31–34.

[9] Cengiz T G, Babalık F C. An on-the-road experiment into the thermal comfort of car seats. Applied Ergonomics 2007; 38: 337–347

[10] Gadi M B. A new computer program for the prediction and analysis of human thermal comfort. Applied Energy 2000; 65: 315–320.

[11] Kolich M. A conceptual framework proposed to formalize the scientific investigation of automobile seat comfort. Applied Ergonomics 2008; 39: 15–27.

[12] Gribok AV, Buller M J., Reifman J. Individualized Short-Term Core Temperature Prediction in Humans Using Biomathematical Models. IEEE Transactions on Biomedical Engineering 2008; 5(55): 1477-1487.

[13] Garcia-Souto MDP, Dabnichki P. Skin temperature distribution and thermoregulatory response during prolonged seating. Building and Environment. 2013 (69): 14-21

[14] McCarthy P W, Liu Z, Heusch A, Cascioli V. Assessment of humidity and temperature sensors and their application to seating Journal of Medical Engineering and Technology 2009; 33: 449 –453.

[15] Liu Z, Cascioli V, Heusch A, McCarthy PW. Studying thermal characteristics of seating materials by recording temperature from 3 positions at the seat-subject interface Journal of Tissue Viability 2011; 20(3): 73-80.

[16] Huang NE, Shen Z, Long SR et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceeding of the Royal Society A, 1998; 454: 903-995.

[17] Huang NE, Shih HH, Shen Z, Long S. The ages of large amplitude coastal seiches on the Caribbean Coast of Puerto Rico. Journal of Physical Oceanography 2000; 30: 2001-2012.

[18] Wu Z., Huang E.N. A study of the characteristics of white noise using the empirical mode decomposition method. Proceedings of the Royal Society of London-A 2004; 460: 1597–1611.

[19] Molla MD, Sumi A., Rahman M. Analysis of temperature change under global warming impact using empirical mode decomposition. International Journal of Information Technology 2006; 3(2):131-139.

[20] Liu Z, Luo Z, Wei J, Liu M, Chen T, Chen L, Heusch AI, Cascioli V, McCarthy PW. Noise Removal Applied to a Temperature Signal from Body and Seat Contact Surface Based on the EMD

Method. International Journal of Signal Processing, Image Processing and Pattern Recognition. 2013; 6(4): 431-440.

[21] Levy A., Kopplin K., Gefen A. An air-cell-based cushion for pressure ulcer protection remarkably reduces tissue stresses in the seated buttocks with respect to foams: Finite element studies. Journal of Tissue Viability 2013; 20(1): 13-23.

[22] Chenu O., Vuillerme N., Bucki M., Diot B., Cannard F., Payan Y. TexiCare: An innovative embedded device for pressure ulcer prevention. Preliminary results with a paraplegic volunteer. Journal of Tissue Viability 2013;22(3): 83-90.

[23] Gefen A. How do microclimate factors affect the risk for superficial pressure ulcers: A mathematical modelling study. Journal of Tissue Viability 2011; 20(3): 81-88.

[24] Stockton L., Gebhardt K.S., Clark M. Seating and pressure ulcers: clinical practice guideline. Journal of Tissue Viability 2009; 18(4): 98-108.

[25] Wall J., Colley T. Preventing pressure ulcers among wheelchair users: preliminary comments on the development of a self-administered risk assessment tool. Journal of Tissue Viability 2003; 13(2): 48-50.