International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol. 6, No. 4, August, 2013

Noise Removal Applied to a Temperature Signal from Body and Seat Contact Surface Based on the EMD Method

Zhuofu Liu[1, a], Zhongming Luo[1], Jiang Wei[1], Meimei Liu[2], Tianye Chen[2], Liang Chen[2], Andrew I Heusch[3], Vincenzo Cascioli[4] and Peter W McCarthy[3]

[1.] *The higher educational key laboratory for Measuring & Control Technology and Instrumentations of Heilongjiang Province, Harbin University of Science and Technology, Harbin, Heilongjiang, 150080, China*

[2.] *The Second Affiliated Hospital of Harbin Medical University, Harbin, Heilongjiang, 150086, China*

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

[4.] *Murdoch University Chiropractic Clinic, Murdoch, 6150, Western Australia*

[a.] *zhuofu_liu@hrbust.edu.cn*

Abstract

People today spend longer seated resulting from changes in demand on the workforce. As a result there is a need for a greater understanding of factors affecting pressure sore formation and comfort in general. In order to monitor the body-cushion interface temperature, we have developed a portable five-channel temperature measuring system which can be powered by a laptop. An Empirical Mode Decomposition (EMD) was used to remove noise of thermal data between body and seat contact surface. The performance of this data driven filter was compared with three other filters (medium filter, adaptive filter and wavelet filter) with the help of the goodness of fitness statistics as judgment criteria. Results showed the EMD-based filter worked better than traditional de-noising algorithms with the lowest RMSE (root-mean-square-error) and the highest R^2 values.

Keywords: *noise suppression; temperature; empirical mode decomposition; cushion*

1. Introduction

With the development of modern technology, intelligent machines and industrial robots have replaced some aspects of work so that people can spend more time in sitting and relaxing than before. As a result, seating comfort has become very important as customer's expectations rise [1, 2].

Climate and temperature factors are commonly referenced sources of patient comfort or discomfort in the literature [3]. Providing thermal comfort to chair users is a priority due to its relevance to ergonomic, service quality and energy consumption requirements [4, 5]. Comfort is also important at the point of sale and can be a competitive advantage in automotive and furniture industries, which are worth billions of pounds annually.

The incentives for understanding body-seat interface properties have focused on reducing pressure sore formation and have tended to be considered as a major factor of pressure sore formation by directly measuring shear force [2]. In addition, Skin temperature and heat transfer rate at the skin surface are considered to be important components of how thermal information is perceived and processed by the nervous system [6]. Although thermal properties of the region between body and seat are considered one of the important factors, this area has not yet been fully explored, to the authors' knowledge.

In the assessment of thermal comfort Zhang et al. [7] recruited 24 subjects who sat on four vehicle seats with chamber (vehicle) temperatures ranging from 15 °C (cool) to 45 °C (warm). A 2nd-order polynomial function was used to measure the dissatisfying percentage to local heat flow in different temperature conditions. They found zero heat flow resulted in the greatest comfort index score at an air temperature of 22 °C. Their analysis showed that offering an optimal seat temperature would improve drivers and passengers comfort feeling by 80 %. Vlaovic *et al.*, [8] launched experiments to study the microclimate changes created by contact surfaces. They found that microclimate may generate either a positive or a negative effect on a seated person. However, only six people participated in the trials and the probes were placed on or in the seats which may have affected their perception and thus affected comfort. In a bid to control car seat temperature, Mihai [9] proposed a fuzzy logic approach to improve the robustness of its thermal behaviour. In the training stage, an artificial neural network was employed to generate a global model. However, interests were only paid to the driver's seat back, although the contact surface between drivers and cushion are less consistent in this region.

To measure thermal properties between human and seat contact surface, a portable body-seat interface temperature data acquisition system was developed in our pilot study [10, 11]. To the authors' knowledge, few studies have been done to remove noise from original temperature data before carrying out further explorations in the field of seat comfort study. In this paper, we focused on the pre-processing part (EMD-based filter) of the temperature data with the aim to maintain both the sensitivity to detect rapid changes in temperature and the capability to measure such changes accurately.

2. System Description and Sensor Assessment

The temperature measuring system comprises temperature sensor circuits, a data acquisition system and a power supply. Constraints on the system due to the position of the sensors, requires it to be small and unobtrusive. As the sensor circuits were to be placed between the body and the surface of the cushion, any detectable sensor would impact on the comfort and therefore affect the person. The size of each temperature sensor circuit was limited within the range of 15×10×1.5 mm (which subjects do not report as being perceptible: unpublished observations).

To acquire the temperature signals in real time, an efficient data acquisition hardware and software was essential. As all five-channel temperature information must be sampled simultaneously, a parallel ADC (analogue-to-digital converting) interface was the most appropriate choice. In the comparison of reliability and stability, the Pico ADC-11/12 was chosen for our application, as it had an 11-channel ADC interface with 12 bits resolution. Under the graphical programming environment of NI Labwindows, a user-friendly interface was developed, which performed device initialization, real-time data storage, off-line analysis and graphical display.

The USB (Universal Serial Bus) has become a standardised and prevalent interface which can provide a 5 V (volts) supply on a single wire that meets the requirements of the chosen sensors. Under these considerations, one USB port was employed as the power supply to the whole temperature measuring system. Since it is difficult to incorrectly attach a USB connector, this was an additional safeguard to prevent our power supply system being affected by a misplug, which is hazardous to electric devices. It is possible to expand this system to allow multiple simultaneous recording to be made by using a multi-channel USB hub.

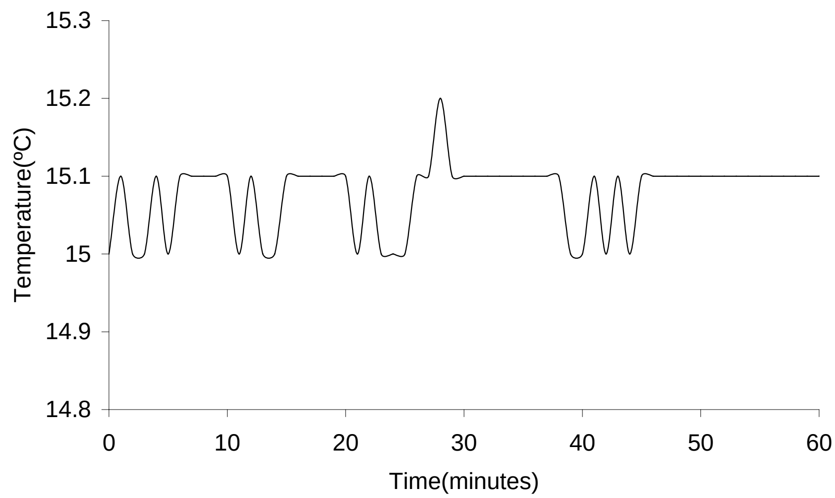

Figure 1. A Single Temperature Sensor's Thermal Pattern was Recorded at 1/60 Hz over 1 Hour

Thermal radiation is electromagnetic radiation emitted from the surface of an object which relates to the object's temperature. Since our interests are about the temperature changes generated by the participants instead of the chips themselves, the infrared camera (Land Instrument, UK) with traceable standardized calibration sources was employed to explore the thermal emission of sensors while in use, to determine if they were likely to contribute significantly to local temperature changes.

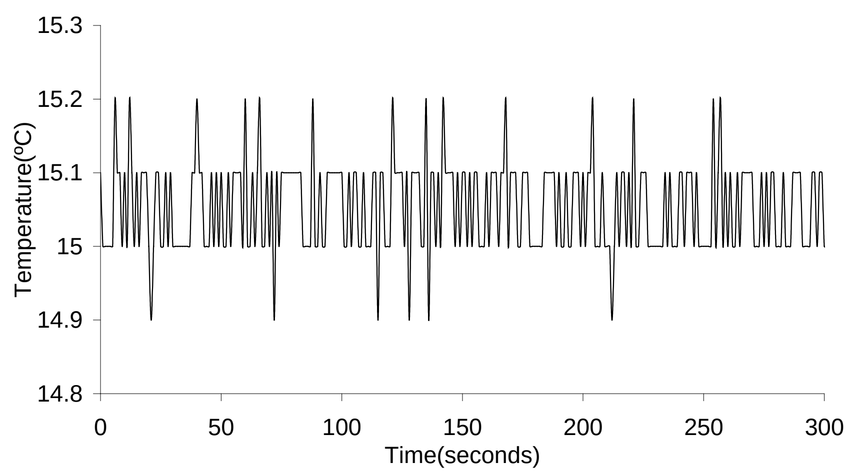

Figure 2. Thermal Radiation of Repeated Experiments over 5 Minutes with Sampling Frequency 1 Hz

After setting up the devices, the door was closed and experiments were launched uninterruptedly to avoid any man-made impacts. To consider a long-term effect, thermal images of a 'cushion' with temperature sensors were recorded every minute for an hour, during which the laboratory room had been vacated to avoid thermal interference from the researchers. Throughout the experiment the temperature of the cushion and sensors varied between 15.0 °C and 15.2 °C (Figure 1). The identical experiment was repeated with sampling frequency of 1 Hz for another five minutes to monitor transient thermal phenomena. Throughout the experiment the temperature of the cushion and sensors varied between 14.9 °C and 15.2 °C (Figure 2).

In the test of sensor consistency, two 25 kg sand bags were placed on the foam cushion to control for the effects of body equivalent pressure alone on the sensors. The whole system was placed in the research room with ambient temperature around 20 ºC and the experiment lasted for an hour. The door of the research room was closed within that period and no personnel entered, therefore is reasonable to assume that any differences between the sensors would be the result of the sensors working inconsistently. Based on Table 1, it can be seen that all five temperature sensors, performed well with the manufacturers advertised maximum difference of 0.6 ºC.

Table 1. Statistical Result of Temperature Sensors in the Consistent Test

	T1	T2	T3	T4	T5
Mean (°C)	20.06	20.10	20.33	19.70	20.07
Median (°C)	20.10	20.10	20.30	19.70	20.10
SD (°C)	0.05	0.02	0.04	0.01	0.05
Min (°C)	20.00	20.10	20.30	19.70	20.00
Max (°C)	20.10	20.20	20.40	19.80	20.10

3. Empirical Mode Decomposition and its Noise Suppression Application

In 1998, Huang *et al.*, [12-14] presented a nonlinear signal processing method called empirical mode decomposition (EMD) for adaptively representing a non-stationary signal as a sum of zero-mean well-behaved fast and slow oscillation modes referred as intrinsic mode functions (IMFs). The procedure of EMD is both efficient and effective, and the main concept is to allow the original data sets to go through a series of so-called sifting procedures. The selection criterion is that the final data series are stationary. The major innovative aspect of the EMD method is the proposal of the IMF functions, which is based on local natural properties of the signal and provides a subsequent meaning to the concept of instantaneous frequency. An IMF can be best defined as a hidden oscillation mode that is embedded in the data series, since it is allowed to be non-stationary and either be amplitude or frequency modulated.

According to Huang *et al.*, [12], an IMF is defined as a function that satisfies the following two conditions:

(1) In the whole data series, the number of local extrema and the number of zero crossings must either equal or differ at most by one;

(2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

To simply depict how the EMD procedure sifts original data series, let us use an arbitrary data series $X(t)$, the sifting process is as follows [12-14]:

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

(2) Calculate the upper envelope $u(t)$ and the lower envelope $v(t)$ with a cubic spline function.

(3) The mean envelope $m(t)$ of the series $X(t)$ is the mean value of the upper and lower envelopes:

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

(4) A new series with low frequency removed is calculated by subtracting the mean envelope from the series $X(t)$:

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

Generally speaking, h_1 is still a non-stationary series, so the above procedure must be repeated *k* times until the mean envelope approximates zero:

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

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

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

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

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

Overall, $c_1(t)$ 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 a 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 predetermined small value or a monotonic function.

Original data comes from 20 minutes of temperature sensor data from a sensor at the seat-human interface while sitting on a foam seat. This data set contained unwanted noise. In order to suppress the oscillation while keeping the veracity of the slowly varying trend in the recording, the noise-polluted signal was fed into the EMD sifting procedure and the outcome includes IMF components as well as one residual signal. To determine which part of the decomposed components may be useful, it is necessary to analyze the EMD outcomes by some theoretical means.

Based on the research results of Wu and Huang [14], Gaussian white noise can be effectively removed with the help of EMD methodology. Through empirical studies, the EMD was proved to be an effective dyadic filter, which appeared adequate at separating the white noise into high frequency IMF components [14-16].

In addition, all IMF components are normally distributed (Figure 3) and the Fourier spectra of the IMF components appear identical in shape (Figure 4). Let f_j ($j = 1, ..., N$) be the Gaussian white noise series, Fourier analysis and synthesis equations can be expressed as [14]:

$$f_j = \mathrm{Re}\left[\sum_{k=1}^{N} F_k \exp\left(i\frac{2\pi jk}{N}\right)\right] = \sum_n C_n(j) \tag{7}$$

$$F_k = \frac{1}{N} \sum_{j=1}^{N} f_j \exp\left(-i \frac{2\pi jk}{N} \right) \quad (8)$$

where $C_n(j)$ is the nth IMF component.

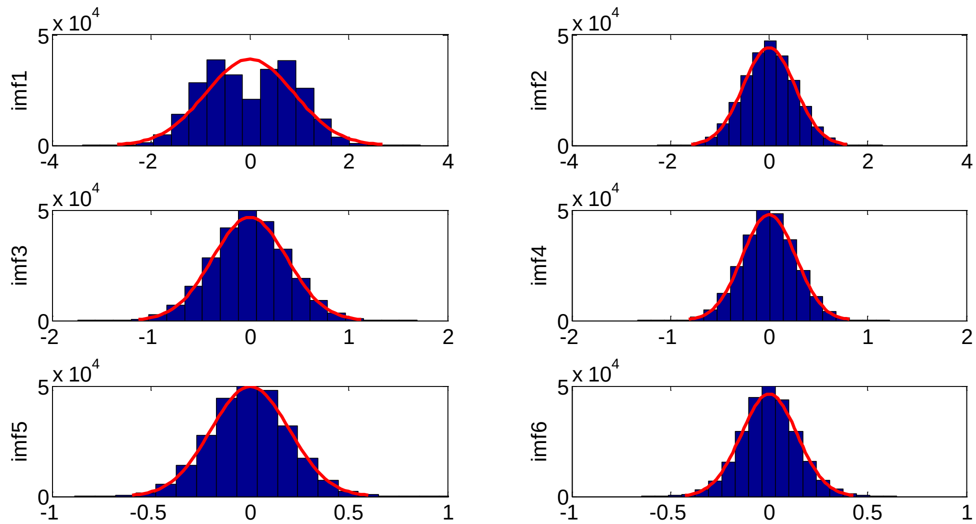

Figure 3. Distribution of the IMF Components for each Level of IMF (1 To 6). An Approximate Normal Distribution has been Overlapped on Each Histogram (In Red). Note the Horizontal Axis Changes in Scale, Indicating the Closer Approximation to the Mean with the Greater the Number Runs through the Method

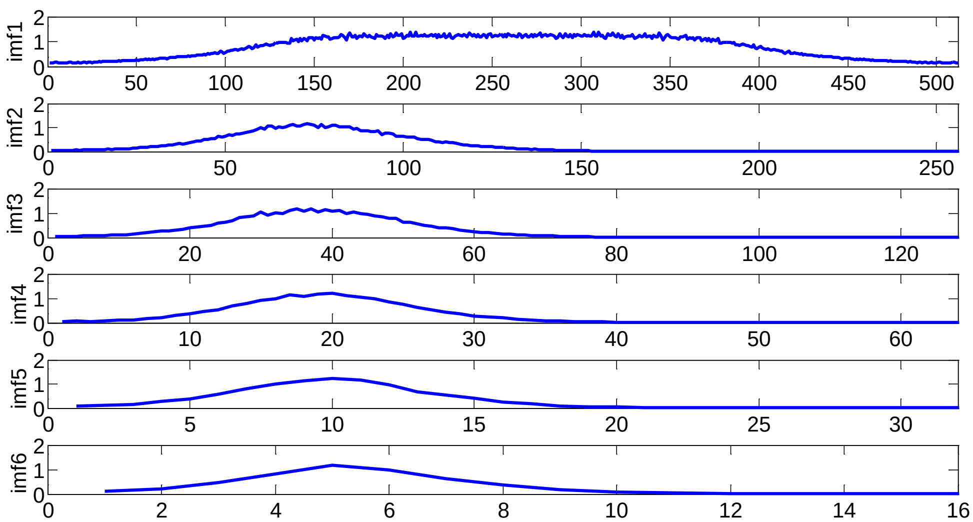

Figure 4. Fourier Spectra of the IMF Components

In our application, the low frequency component (referred to as the residue) was kept as the noise free signal for further analysis as temperature between body and seat interface often changes very slowly. The filtering process is illustrated in Figure 5 [16].

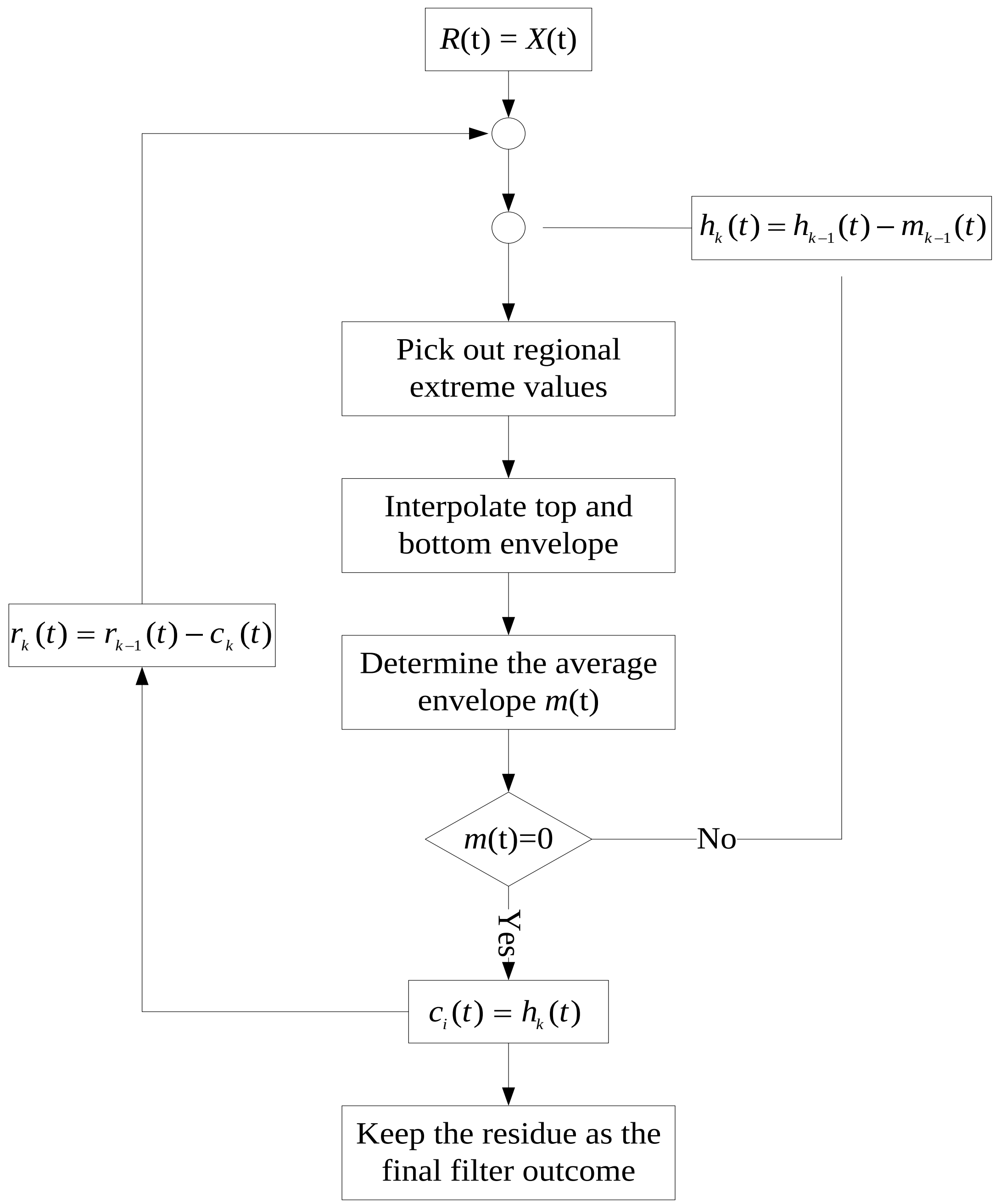

Figure 5. Flowchart of the EMD-Based Filter Which includes the Sifting Process and Noise Removal Function

4. Filter Performance Comparison

Temperature data sets of body-seat interface were used to evaluate the methods' capability of suppressing noise. The data sets include 50 subjects (30 male and 20 female with age range between 19 and 22 years) who had volunteered to take part in the 20 minute sitting experiments. These raw data were de-noised using either of the filters: medium filter, adaptive filter, wavelet filter or EMD-based filter.

Table 2. Performance Comparison of Different Filters

Noise removal method	Temperature	
	RMSE	R^2
Medium filter	1.34	0.89
Adaptive filter	1.71	0.78
Wavelet filter	1.02	0.93
EMD-based filter	0.73	0.99

In the quantitative assessment, the goodness of statistical fit was calculated using RMSE (root-mean-square error) and R^2. Table 2 shows the averaged statistics of all 50 subjects, indicating that the EMD-based filter has the lowest RMSE and highest R^2 values. From this we can conclude that the EMD-based filter outperforms other traditional noise suppression algorithms.

5. Conclusion

In this paper, an EMD-based filter was applied to suppress the noise in thermal data acquired at the interface between cushion and body. Comparison trials were carried out to assess the data smoothing ability of an EMD-based filter against three classic filters (medium filter, adaptive filter and wavelet filter). Statistical analysis showed the EMD-based filter to have stronger noise removal capability while retaining the important features of the original data in relation to interpretation of temperature profile at the body-cushion interface.

In future work, humidity data which contains piece-wise abrupt changes will be examined as it is another essential index in the objective measurement of sitting comfort.

Acknowledgements

This work was supported by Harbin Scientific Innovation Project for Elite Young Researchers (Grant No. 2013RFQXJ003), Key Research Project of Heilongjiang Province (Grant number: GZ11A403), Scientific Project of Heilongjiang Education Department (Grant number: 12511201) and Master Student Innovation Program of Heilongjiang Province (Grant number: YJSCX2012-109HLJ).

References

[1] T. Gündüz Cengiz and F. C. Babalık, “An On-the-road Experiment into the Thermal Comfort of Car Seats”, Applied Ergonomics, vol. 38, **(2007)**, pp. 337–347
[2] M. Kolich, “A Conceptual Framework Proposed to Formalize the Scientific Investigation of Automobile Seat Comfort”, Applied Ergonomics, vol. 39, **(2008)**, pp. 15–27.
[3] P. Vink “Editorial: Comfort and Discomfort Studies Demonstrate the Need for A New Model”, Applied Ergonomics, vol. 43, **(2012)**, pp. 271-276.
[4] H. Oi, K. Tabata, Y. Naka, A. Takeda and Y. Tochihara, “Effects of Heated Seats In Vehicles on Thermal Comfort During the Initial Warm-Up Period”, Applied Ergonomics, vol. 43, **(2011)**, pp. 360-367
[5] T. P. Lin, R. L. Hwang, K. T. Huang, C. Y. Sun and Y. C. Huang, “Passenger Thermal Perceptions, Thermal Comfort Requirements, and Adaptations in Short- and Long-Haul Vehicles”, International Journal of Biometeorology, vol. 54, **(2011)**, pp. 221-230.
[6] T. Sakoi, K. Tsuzuki, S. Kato, R. Ooka, D. Song and S. Zhu, “Thermal Comfort, Skin Temperature Distribution, and Sensible Heat Loss Distribution In The Sitting Posture in Various Asymmetric Radiant Fields”, Building and Environment, vol. 42, **(2007)**, pp. 3984-3999.
[7] Y. F. Zhang, D. P. Wyon, L. Fang and A. K. Melikov, “The Influence of Heated or Cooled Seats on the Acceptable Ambient Temperature Range”, Ergonomics, vol. 50, **(2007)**, pp. 586-600
[8] V. Zoran, D. Danijela and G. Ivica, “Research of temperature and moisture during sitting on office chairs”, Drvna Industrija, vol. 63, **(2012)**, pp. 105-112.

[9] M. Dan, “Fuzzy Control for Temperature of the Driver Seat in a Car”, Proceeding of 2012 International Conference on Applied and Theoretical Electricity, Craiova, Romania, **(2012)** October 25-27
[10] P. McCarthy, Z. Liu, A. I. Heusch and C. Vincenzo, “Assessment of Humidity and Temperature Sensors and Their Application to Seating”, Journal of Medical Engineering & Technology. vol. 33, **(2009)**, pp. 449-453.
[11] Z. Liu, V. Cascioli, A. I. Heusch and P. W. McCarthy, “Studying Thermal Characteristics of Seating Materials by Recording Temperature from 3 Positions at the Seat-Subject Interface”, Journal of Tissue Viability, vol. 20, **(2011)**, pp. 73-80
[12] N. E. Huang, Z. Shen and S. R. Long, “The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-Stationary Time Series Analysis”, Proceeding of the Royal Society A, vol. 454, **(1998),** pp. 903-995.
[13] N. E. Huang, H. H. Shih, Z. Shen and S. Long, “The Ages of Large Amplitude Coastal Seiches on the Caribbean Coast of Puerto Rico”, Journal of Physical Oceanography, vol. 30, **(2000)**, pp. 2001-2012.
[14] Z. Wu and N. E. Huang, “A Study of the Characteristics of White Noise Using the Empirical Mode Decomposition Method”, Proceedings of the Royal Society of London-A, vol. 460, **(2004)**, pp.1597-1611.
[15] P. Flandrin, P. Gonc Alves and G. Rilling, “Detrending and Denoising with Empirical Mode Decompositions”, 12th European Signal Processing Conference, **(2004)**, pp. 1581-1584
[16] Z. Liu, Z. Luo, A. I. Heusch, V. Cascioli and P. W. McCarthy, “Removal of Noise from the Body-Seat Interface Temperature Signal Using Empirical Mode Decomposition”, Proceeding of 4th International Symposium on Computational Intelligence and Industrial Applications, **(2010)**, pp.94-102