Intelligent Environments 2018
I. Chatzigiannakis et al. (Eds.)

doi:10.3233/978-1-61499-874-7-168

Toward a Real-Time and Physiologically Controlled Thermal Comfort Provision in Office Buildings

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Abstract
Thermal comfort is, by definition, a personal and subjective psychological sensation. Still, its provision in office buildings relies on underperforming and energy-hungry Heating Ventilation and Air Conditioning (HVAC) units that preclude people's personal preferences. This leads to people reporting a high discontent with the built environment. This study provides a preliminary evaluation of a physiologically controlled thermal comfort provision based on Pulse Rate Variability (PRV). The study is based on a premise that thermally uncomfortable environments affect temperature homeostasis in humans. This change in homeostasis is indirectly detected by e.g. the variability of the heart's beat-to-beat intervals. We experimented on a user sitting in two thermal environments (cold and neutral) to estimate PRV via a photoplethysmogram (PPG) signal recorded on his wrist. The result of the experiment shows that it is possible to predict the user's thermal state in real-time with an accuracy exceeding 90%. Hence, the paper constitutes a prima facie evidence of the possibility of designing real-time physiologically controlled thermal conditioning systems.

Keywords. thermal comfort, smart thermostats, heart rate variability, pulse rate variability, smart building, personal thermal comfort, humanized computing

1. Introduction

The provision of thermal comfort in buildings is mostly based on mechanical Heating Ventilation and Air Conditioning (HVAC) systems that, in a nutshell, hinge on controlled laboratory experiments and consider environmental parameters (e.g. air temperature, air velocity, mean radiant temperature and relative humidity) and personal factors (e.g. metabolic rate and clothing insulation) to predict a uniform thermal environment that, purportedly, is satisfactory to all occupants [1]. In practice, however, HVAC systems fails to live up to their expectations since people report a high thermal comfort dissatisfaction in buildings [2]. This dissatisfaction is expected because HVAC systems are based on mathematical models derived from experiments on a large group of people. On the contrary, by definition, thermal comfort is "a condition of mind that expresses satis-

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faction with the thermal environment and is assessed by subjective evaluation" [3], and is trigged by psychological and behavioral factors, and depends on people's norms and their expectations [4, 5]. As a result, it varies from one person to another [6]. It is, thus, a complex phenomenon that cannot be reduced to simple linear mathematical equations [7]. Moreover, HVAC units necessitate enormous energy in order to create its sine qua non thermal neutral conditions. Paradoxically, there is credible evidence that there exist no one-fits-all thermal comfort settings that would satisfy all occupants. Instead, there is a wide variation of satisfactory thermal comfort settings amongst people [8, 7], with e.g. acceptable temperature ranging between 18 °C and 28 °C in Japan [9], and, in extreme cases, can be even extended to between 10 °C and 35 °C [4]. Henceforth, achieving thermal neutrality is a costly and meretricious undertaking that is not necessarily the right way to provide thermal comfort.

Recent research, partly due to an increased awareness of the need for a sustainable energy consumption, propose to use personalized environmental conditioning systems [10, 8] as a compromise between thermal comfort and energy conservation. Personalized conditioning systems deliver the thermal comfort to the parts of the body where it is needed the most and allow occupants to extend their thermostat's dead-bands beyond ranges that would be otherwise prescribed by conventional thermal comfort models; therefore, they necessitate considerably lower energy without compromising people's thermal comfort [10]. Nevertheless, they have a lower adoption and acceptance rate presumably due to the required user interaction that can lead to rebounds and overshoots [10]. Another research trend is the use of occupancy-based intelligent thermal controllers [11, 12]. In essence, they adaptively dispense heating or cooling depending on the availability, or the lack thereof, of building occupants. However, while they provide a good energy saving [13], their performance is comparable to that already achievable by existing systems [14]. Additionally, like existing HVACs, they do not account for differences amongst people, their thermal preferences, their mental state and other psychometrics that influence thermal comfort. Recently, Barrios and Kleiminger [15] proposed an intelligent thermostat that infers thermal comfort from a combination of occupants' heart rates and their surrounding environment and they achieved a ± 0.5 point accuracy within the expected ASHRAE scale. Their infrastructure, however, requires periodic manual calibration from the users. The past few years have seen an increasing interest in the possibility of creating personalized thermal comfort systems that predict an individual's thermal needs based on the data collected in his surrounding. In an effort to provide a cohesive guidance to researchers in this emerging research area, Kim and her coauthors [16] recently proposed a personal comfort model that leverage the Internet of Things (IoT) and machine learning to learn and predict an individual's thermal comfort requirements and showed that the model is noticeably accurate compared to the widely used Predicted Mean Vote (PMV) model [17].

In our previous research we asserted that since, in humans, thermal regulation is controlled by involuntary mechanisms governed by the brain's hypothalamus [18], people's thermal comfort could be more rigorously estimated from the variation of their physiological signals. We showed that it was possible to predict, with a 93.7% accuracy, subjects' thermal comfort state using heart rate variability (HRV) [19] and we proposed a generic framework for a collective energy-efficient physiologically-controlled system that could be used in e.g. office environments [20]. This paper is a natural continuation of our previous works and presents a glimpse of the possibility of creating a real-time physiologically controlled thermal conditioning systems based on PRV.

2. Methods

2.1. Machine learning model

To predict thermal comfort, we conducted experiments on 17 male subjects doing light work (metabolic rate $\approx$1.0) in three thermal chambers whose settings conform to those of a cold, a neutral and a hot thermal sensation on a PMV index scale (Table 1). Each experiment lasted for about 30 minutes. For each environment, we recorded each subject's electrocardiogram (ECG). These ECG signals were used to extract inter-beat interval (IBI) signals that were subsequently used to compute HRV indices. In this study, we selected only time domain HRV indices that require a modest time complexity (Table 2). All HRV indices were computed as stated by the recommendations of the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [21] on a window segment of 5 minutes long IBI signal. A new IBI sample is added to the segment (while the oldest one is removed) and new HRV indices are calculated. This process is repeated until the end of the entire IBI signal.

Table 1. Thermal chamber settings††

	cold	neutral	hot
activity level	1	1	1
clothing level	1	1	1
air temperature(°C)	18.0	24.0	30.0
radiant temperature(°C)	18.0	24.0	30.0
air speed (m/s)	0.3	0.3	0.3
humidity (%RH)	50.0	65.0	80.0
PMV index†	-1.79	-0.03	+1.87

†PMV adjusted for the cooling effect of an elevated air speed

†† Table adapted from an experiment in [19].

Unlike in our previous work [19], in which we evaluated a machine learning model for each user, in this study, the objective was to create a generic model that could be used to predict people's thermal comfort with little or no calibration. In order to achieve this, the extracted HRV indices of all subjects in all thermal environments were combined and shuffled. The resulting data samples were thereafter split into a training and testing set using a 10-fold cross validation, i.e. each of the 10 folds is used to train a random forest classifier on the remaining 9 folds. The resulting model is later used to predict the perceived thermal comfort status in real-time.

We evaluated the performance of the model by computing its precision, recall and F1-score and the support for each class. The precision expresses the proportion of classified true positives (TP) vis-à-vis that of the false negative (FP) in the whole dataset (Equation 7) while the recall expresses the proportion of samples that were misclassified as true, i.e. that are false negative (FN) in the dataset (Equation 8)

Table 2. Description of the selected HRV indices

HRV index	Short description	Equation
MEAN_RR	Mean of all RR intervals	
MEDIAN_RR	Median of all RR intervals	
SDRR	Standard deviation of all interval	
RMSSD	Square root of the mean of the sum of the squares of the difference between adjacent RR intervals	$\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1}-RR_i)^2}$ (1)
SDSD	Standard deviation of all interval of differences between adjacent RR intervals	$\sigma(RR_{n+1}-RR_n)$ (2) †
SDRR_RMSSD	Ratio of SDRR over RMSSD	
HR	Heart Rate measured by the number of heart beats per minute	
pNN25	Percentage of adjacent RR intervals differing by more than 25 ms	$\frac{\sum_{i=1}^{N}\left(\lvert R_i-R_{i+1}\rvert>25ms\right)}{N-1}$ (3)
pNN50	Percentage of adjacent RR intervals differing by more than 50 ms	$\frac{\sum_{i=1}^{N}\left(\lvert R_i-R_{i+1}\rvert>50ms\right)}{N-1}$ (4)
SD1	Poincaré plot descriptor of the short-term heart rate variability	$\sqrt{variance\left(\frac{RR_i-RR_{i+1}}{\sqrt{2}}\right)}$ (5)
SD2	Poincaré plot descriptor of the long-term heart rate variability	$\sqrt{variance\left(\frac{RR_i+RR_{i+1}}{\sqrt{2}}\right)}$ (6)
KURT	Kurtosis of all RR intervals	ref. to note §
SKEW	Skewness of all RR intervals	ref. to note ⋇
MEAN_REL_RR	Mean of all relative RR intervals	ref. to note ‡
MEDIAN_REL_RR	Median of all relative RR intervals	ref. to note ‡
SDRR_REL_RR	Standard deviation of all relative RR interval	ref. to note ‡
RMSSD_REL_RR	Square root of the mean of the sum of the squares of the difference between adjacent relative RR intervals	ref. to eq. 1 and note ‡
SDSD_REL_RR	Standard deviation of all interval of differences between adjacent relative RR intervals	ref. to eq. 2 and note ‡
SDRR_RMSSD_REL_RR	Ratio of SDRR_REL over RMSSD_REL	
KURT_REL_RR	Kurtosis of all relative RR intervals	ref. to notes § and ‡
SKEW_REL_RR	Skewness of all relative RR intervals	ref. to notes ⋇ and ‡

† $\sigma(x)=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2}$, N is the length of the signal

§ $KURTOSIS(x)=\frac{E\left(x-\bar{x}\right)^4}{\sigma(x)^4}$,
where $\bar{x}$ is the mean of x and E(k) the expected value of k

⋇ $SKEWNESS(x)=\frac{E\left(x-\bar{x}\right)^3}{\sigma(x)^3}$,
where $\bar{x}$ is the mean of x and E(k) the expected value of k

‡ $REL_{RR_i}=2\left(\frac{RR_i-RR_{i-1}}{RR_i+RR_{i-1}}\right),\quad i=2,\ldots,N$ [22]

$$precision = \frac{TP}{TP+FP} \tag{7}$$

$$recal = \frac{TP}{TP+FN} \tag{8}$$

The F1 score is a harmonic mean of the precision and the recall metrics (Equation 9)

$$F1 - score = 2\frac{presion \times recall}{precision + recal} \tag{9}$$

2.2. Real-time thermal comfort prediction experiment

In this preliminary study, we evaluated one subject whose IBI signal was extracted via a photoplethysmography (PPG) signal recorded using an Empatica E4 wristband (Empatica, Milano, Italy). The blood volume pulse (BVP) signal is obtained by shining a combination of red and green lights on the skin of the wearer of the device. The skin absorbs most of the lights but some is reflected back. The ratio between the reflect and absorbed light depends on the changes in the blood flow due to the activity of the heart and is used to detect the heart beat pattern [23]. The Empatica E4 wristband's photoplethysmography utilizes a green light to detect the heart beat patterns and a red light to track down and reduce hand motion artifacts [24]. The extracted IBI signal is used to predict the thermal comfort of the user using a random forest machine learning model outlined in section 2.1. While this model was trained using IBI extracted from an ECG signal, the thermal comfort prediction is based on an IBI signal extracted from a photoplethysmography pulse rate. This is because the recording of an ECG signal would have required obtrusive chest-strapped ECG electrodes. However, the use of a PPG wristband is non-invasive and can be easily used in a typical office environment. It is important to note that the PPG signal and the ECG signal are not the same. However, PRV is highly correlated with HRV and could be used as its surrogate [25] especially when studying time domain HRV [26]. Nevertheless, PPG is not as precise as ECG. Furthermore, wrist-worn PPG devices are accurate only at rest and their performance decreases when there are excessive hand motions [27]. As a result, our experiment required the subject to sit still in a simulated office environment and refrain from sudden hand motions. In this preliminary study, we only tested two thermal environments: the cold and the neutral. Before the experiment, the user sat in an air conditioned room and was given a remote control to modify the room temperature until the user indicated that he felt cold or neutral depending on the environment under study. At this point, the user was given an Empatica E4 wristband that he wore on his left hand and requested to read some news on a computer. During the subsequent 30 minutes, the Empatica E4 wristband was used to record the subject's PPG signal which is sent to an Android application via Bluetooth wireless technology (Figure 1). An IBI signal is extracted from the received PPG signal and is fed to the machine learning model and the predicted environment is logged to a file for further analysis. In this experiment, we presumed that the user's initial thermal comfort sensation would stay the same during the duration of the experiment. This might be the case for a short period but may not be necessarily the case for a prolonged period.

Figure 1. Real-time thermal comfort prediction system —An Empatica E4 wristband is used to record a photoplethysmogram (PPG) signal. An inter-beat interval (IBI) signal is extracted from the PPG, sent to a smartphone, and used to calculate pulse rate variability indices (PRV). These indices are thereafter used to predict, in real-time, the comfort state of the wearer of the E4 device

3. Results and discussion

Thermal comfort is subjective and depends on, inter alia, the psychometrics and the biological makeup of the person. We asserted that it could be more rigorous to infer the person's thermal comfort from the variation of his biological signals that are normally altered when the person is thermally dis-comfortable. This study is limited to heart rate variability since we had previously shown it to change when the subjects were in thermally dis-comfortable environments [19]. The trained classifier achieved a very high classification performance and there was relatively very few misclassifications (Table 3). What's more, a 99% accuracy can be achieved using less than 5000 training samples

Table 3. Model performance evaluation metrics

	precision	recall	F1-score	support
Cold	100	100	100	5054
Neutral	99.99	99.9	99.9	5103
Hot	100	99.96	99.98	5123
Average	99.99	99.99	99.99	15280

(Figure 2). This suggests that people's thermal comfort can be deducted from a short segment of their IBI signal. It is also important to note that a few HRV features (MEADIAN RR, MEAN RR and HR) are more important in classifying thermal comfort (Figure 3).

This might be helpful in cases where computing many HRV features is not computationally feasible.

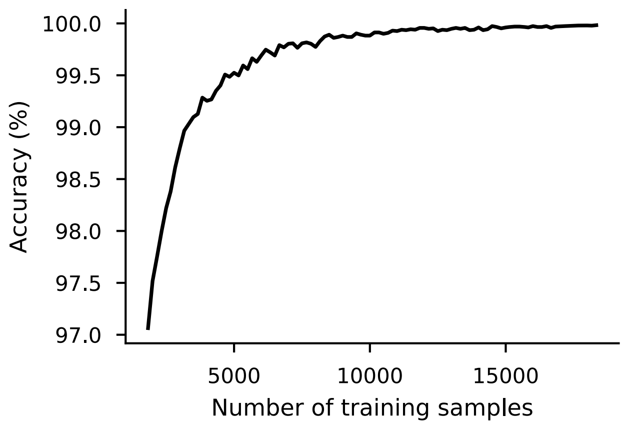

Figure 2. The prediction accuracy of the machine learning model achieve an acceptable performance even with a relatively small training samples

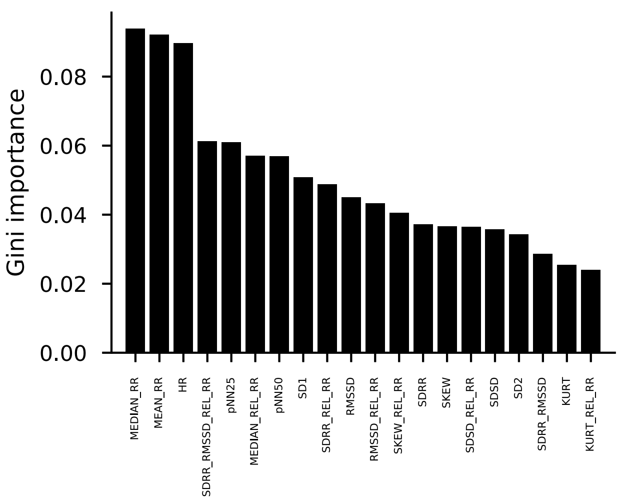

Figure 3. HRV feature importance based gini impurity index used for the calculation of splits during training shows that a few features (MEAN RR, MEADIAN RR and HR) are disproportionately more important for the thermal comfort prediction

Furthermore, since thermal comfort is a subjective sensation, in our experiment, we requested the user to manually vary the thermostat himself until he felt cold or neutral. By this approach, unlike arbitrary thermal comfort settings that are normally used without the individual's saying, the user can adjust the temperature to a level that is satisfactory to him. At the end of the experiment, we analyzed a log file containing the predicted comforts states, and it was found that the model could achieve a high accuracy (96.53% and 92.30% accuracy in the cold and neutral environment respectively). Moreover, the subject indicated he felt thermally comfortable at 27 °C. This is relatively higher than the normal temperature dictated by office HVAC units and is a good indicator that energy could be saved, for example in the summer, by elevating indoor temperatures depending on the thermal tolerance of its occupants. This experiment is however very limited in nature (only one user and in two thermal comfort environmental settings) and not conclusive. A more exhaustive experiment is required to prove the veracity of these findings.

4. Conclusion and future work

The prima facie results of this study highlight the possibility of designing thermal comfort provision systems that are based on the variation of people's physiological signal due to the change in the thermal environment. We showed that it is possible to predict thermal comfort based on the variability of the pulse rate. We surmise our proposed method provide the following advantages over existing methods:

- Higher thermal comfort prediction accuracy —existing thermal provision methods are capped at around 80% thermal satisfaction rate [28]. Our proposed approach might achieve a higher satisfaction rate since it provides a personalized thermal comfort based on how the person 'feels'.
- Reduction in energy consumption required for thermal comfort provision —since people have different thermal comfort expectations, it could be possible to swing the thermostat's deabands away from the traditional limits. This approach has the potential to significantly reduce the energy consummation [29] without affecting building occupants' thermal comfort.
- Such a physiologically controlled system could also be used as part of a responsive and healthy smart office to detect e.g office occupants' psychosocial stress [30] and for chronic diseases detection and prognosis [31].

At this stage, however, the results of this study are not conclusive. Further experiments are needed to assert the validity of this approach. Ideally, the study would be conducted on a large group of people, of all genders and age and be conducted in thermal settings similar to those of the ASHRAE PMV scale (hot, warm, slightly warm, neutral, slightly cool, cool and cold). There is also a need to compare a model extracted from an ECG signal with that extracted from a PPG signal and assess which one works well for thermal comfort prediction. In the future, we also plan to estimate the predicted comfort based on a majority vote of preceding predictions. This would reduce wrong predictions and improve the robustness of the system.

References

[1] R. J. de Dear, T. Akimoto, E. A. Arens, G. Brager, C. Candido, K. W. D. Cheong, B. Li, N. Nishihara, S. C. Sekhar, S. Tanabe, J. Toftum, H. Zhang, and Y. Zhu, "Progress in thermal comfort research over the last twenty years", *Indoor Air*, vol. 23, no. 6, pp. 442–461, Dec. 2013.

[2] International Facility Management Association, “Temperature Wars: Savings vs. Comfort”, International Facility Management Association, Houston, Tech. Rep., 2009, pp. 1–7.

[3] ASHRAE, “ANSI/ASHRAE 55 Thermal Environmental Conditions for Human Occupancyl”, vol. 2010, p. 42, 2010.

[4] J. F. Nicol and S. Roaf, “Rethinking thermal comfort”, *Build. Res. Inf.*, no. Table 1, pp. 1–5, Mar. 2017.

[5] T.-P. Lin, R. de Dear, and R.-L. Hwang, “Effect of thermal adaptation on seasonal outdoor thermal comfort”, *Int. J. Climatol.*, vol. 31, no. 2, pp. 302–312, Feb. 2011.

[6] I. Nastase, C. Croitoru, and C. Lungu, “A Questioning of the Thermal Sensation Vote Index Based on Questionnaire Survey for Real Working Environments”, *Energy Procedia*, vol. 85, no. November 2015, pp. 366–374, 2016.

[7] R. de Dear, “Revisiting an old hypothesis of human thermal perception: alliesthesia”, *Build. Res. Inf.*, vol. 39, no. 2, pp. 108–117, Apr. 2011.

[8] G. S. Brager, H. Zhang, and E. Arens, “Evolving opportunities for providing thermal comfort”, *Build. Res. Inf.*, vol. 43, no. 3, pp. 274–287, 2015.

[9] H. B. Rijal, M. A. Humphreys, and J. F. Nicol, “Towards an adaptive model for thermal comfort in Japanese offices”, *Build. Res. Inf.*, vol. 45, no. 7, pp. 717–729, 2017.

[10] M. Vesely and W. Zeiler, “Personalized conditioning and its impact on thermal comfort and energy performance - A review”, *Renew. Sustain. Energy Rev.*, vol. 34, pp. 401–408, 2014.

[11] J. Ranjan and J. Scott, “ThermalSense: determining dynamic thermal comfort preferences using thermographic imaging”, *Proc. 2016 ACM Int. Jt. Conf. Pervasive Ubiquitous Comput. - UbiComp ’16*, pp. 1212–1222, 2016.

[12] P. X. Gao and S. Keshav, “SPOT: A Smart Personalized Office Thermal Control System”, *Proc. fourth Int. Conf. Futur. energy Syst. - e-Energy ’13*, p. 237, 2013.

[13] L. Nikdel, K. Janoyan, S. D. Bird, and S. E. Powers, “Multiple perspectives of the value of occupancy-based HVAC control systems”, *Build. Environ.*, vol. 129, pp. 15–25, 2018.

[14] W. Kleiminger, F. Mattern, and S. Santini, “Predicting household occupancy for smart heating control: A comparative performance analysis of state-of-the-art approaches”, *Energy Build.*, vol. 85, pp. 493–505, 2014.

[15] L. Barrios and W. Kleiminger, “The Comfstat - Automatically sensing thermal comfort for smart thermostats”, *2017 IEEE Int. Conf. Pervasive Comput. Commun. PerCom 2017*, pp. 257–266, 2017.

[16] J. Kim, S. Schiavon, and G. Brager, “Personal comfort models – A new paradigm in thermal comfort for occupant-centric environmental control”, *Building and Environment*, 2018.

[17] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, and G. Brager, “Personal comfort models: Predicting individuals’ thermal preference using occupant heating and cooling behavior and machine learning”, *Building and Environment*, vol. 129, pp. 96–106, 2018.

[18] S. F. Morrison, “Central neural pathways for thermoregulation”, *Front. Biosci.*, vol. 16, no. 1, p. 74, 2011. arXiv: `NIHMS150003`.

[19] K. N. Nkurikiyeyezu, Y. Suzuki, and G. F. Lopez, “Heart rate variability as a predictive biomarker of thermal comfort”, *J. Ambient Intell. Humaniz. Comput.*, pp. 1–13, Aug. 2017.

[20] K. Nkurikiyeyezu, Y. Suzuki, P. MAret, G. Lopez, and K. Itao, “Conceptual design of a collective energy-efficient physiologically-controlled system for thermal comfort delivery in an office environment”, *SICE J. Control. Meas. Syst. Integr.*, in press.

[21] Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology, “Heart Rate Variability : Standards of Measurement, Physiological Interpretation, and Clinical Use”, *Circulation*, vol. 93, no. 5, pp. 1043–1065, Mar. 1996.

[22] M. Vollmer, “A robust, simple and reliable measure of heart rate variability using relative RR intervals”, in *2015 Comput. Cardiol. Conf.*, vol. 42, IEEE, Sep. 2015, pp. 609–612.

[23] J. E. Sinex, “Pulse oximetry: Principles and limitations”, *Am. J. Emerg. Med.*, vol. 17, no. 1, pp. 59–66, 1999.

[24] Empatica, *Utilizing the PPG/BVP signal*, 2016. (visited on 01/10/2018).

[25] E. Gil, M. Orini, R. Bailón, J. M. Vergara, L. Mainardi, and P. Laguna, “Photoplethysmography pulse rate variability as a surrogate measurement of heart rate variability during non-stationary conditions.”, *Physiol. Meas.*, vol. 31, no. 9, pp. 1271–90, Sep. 2010.

[26] P. Dehkordi, A. Garde, W. Karlen, D. Wensley, J. M. Ansermino, and G. A. Dumont, “Pulse rate variability compared with heart rate variability in children with and without sleep disordered breathing”, in *2013 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 2013, IEEE, Jul. 2013, pp. 6563–6566.

[27] J. Pietilä, S. Mehrang, J. Tolonen, E. Helander, H. Jimison, M. Pavel, and I. Korhonen, “Evaluation of the accuracy and reliability for photoplethysmography based heart rate and beat-to-beat detection during daily activities”, in *EMBEC NBC 2017 Jt. Conf. Eur. Med. Biol. Eng. Conf. Nord. Conf. Biomed. Eng. Med. Phys.*, H. Eskola, O. Väisänen, J. Viik, and J. Hyttinen, Eds., ser. IFMBE Proceedings, Singapore: Springer Singapore, 2017, pp. 145–148.

[28] E. Arens, M. A. Humphreys, R. de Dear, and H. Zhang, “Are ’class A’ temperature requirements realistic or desirable?”, *Build. Environ.*, vol. 45, no. 1, pp. 4–10, 2010.

[29] T. Hoyt, E. Arens, and H. Zhang, “Extending air temperature setpoints: Simulated energy savings and design considerations for new and retrofit buildings”, *Build. Environ.*, vol. 88, no. September, pp. 89–96, Jun. 2015.

[30] P. Melillo, M. Bracale, and L. Pecchia, “Nonlinear Heart Rate Variability features for real-life stress detection. Case study: students under stress due to university examination.”, *Biomed Eng Online*, vol. 10, no. 1, p. 96, 2011.

[31] G. E. Prinsloo, H. L. Rauch, and W. E. Derman, “A Brief Review and Clinical Application of Heart Rate Variability Biofeedback in Sports, Exercise, and Rehabilitation Medicine”, *The Physician and Sportsmedicine*, vol. 42, no. 2, pp. 88–99, May 2014.