A novel approach based on EEG Entropy measurement for indoor human thermal comfort estimation

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Abstract. This paper presents a methodology for the application of electroencephalographic (EEG) Entropy measurements for indoor thermal comfort estimation. Wearables have been demonstrated to be capable of providing accurate physiological measurements to interpret individual thermal responses. Several studies demonstrated the correlation between the EEG Power Spectrum Density (PSD) variation and the subjects' responses exposed to different ambient temperatures. We present a complementary approach based on Approximate Entropy (ApEn) of EEG as a measure for the predictability of EEG series in describing the human thermal condition. We analysed the ApEn of EEG signals acquired from 24 subjects, exposed to three different temperatures (cold: 16°C; neutral: 25°C; warm: 33°C) in a controlled environment, by 4-channels wearable EEG sensors (256 Hz sampling frequency). Statistical analysis showed for both anterior frontal and temporoparietal sites significant differences between neutral, cold, and warm conditions, with a higher value of ApEn in the neutral one. In the anterior frontal area, there was a significative trend of ApEn with smaller values from the neutral to the warm condition, with the cold intermediate. The outcome opens the scenario up to innovative measurement systems, based on wearable EEG devices, for the application of personal comfort models to indoor environmental monitoring and control.

1 Introduction

The interaction between occupants and buildings is a crucial subject largely investigated in the last decades, pointing at preserving humans' well-being with minimized energy consumptions [1]. Several studies demonstrated that thermal comfort impacts on human health, well-being [2], work productivity [3], and consequently on the buildings' energy demand [4,5]. Two main models standardize and assess indoor thermal comfort in buildings: predicted mean vote (PMV) and adaptive models [6]. The PMV, developed through laboratory experiments by Fanger [7], which represents the actual basis of the standard ISO 7730 [8] and ASHRAE 55 [9], expresses occupants' thermal comfort as the result of the heat transfer between the human body and its surrounding environment. Instead, the adaptive model considers the ability of occupants to adapt to an environmental condition in naturally-ventilated buildings, furnishing a linear relationship between an optimal indoor temperature and prevailing outdoor temperature [10]. Despite their widespread adoption, both models present several limitations when applied to comfort management in buildings. In both of the cases, those models have been shown to have a decreasing accuracy in predictive performances when applied to individuals [11,12], because they are aggregate models, aimed at predicting the average comfort of a large population without considering the variation in thermal perception between people. In addition, they do not adapt or re-learn, they are based on fixed input data, from the laboratory (PMV) or the field (adaptive) measurements, which means they are not able to accurately describe the comfort characteristic of individual occupants in a particular field setting. Lastly, both of the models do not allow for the inclusion of some other relevant and influencing factors (e.g., sex, body mass index, age, psycho-physiological status, etc), thus reducing the potential to improve the predictive accuracy of human thermal states. Recently, the concept of *personal comfort models (PCM)* has been introduced to overcome the drawbacks mentioned above. A PCM predicts the individual's thermal comfort response based on the collection of (i) direct feedback from occupants (thermal perception, preference, and comfort), (ii) physiological measurements, and (iii) environmental data, with the capability to adapt as new data is introduced to the model [13]. Recent studies [14–17] proposed a promising solution to predict the comfort of each occupant based on the usage of wearable sensors for physiological measurements paired with environmental sensors [18]. Despite their comfortable design, optimal for real-life application, wearable devices are more prone to collect artefacts, leading to increasing the risk of having less accuracy of the collected data [19]. Among physiological signals, measurable via wearable devices, the EEG has instigated interest, in the field of thermal comfort, for the possibility of measuring the human physiological responses' changes in real-time [20]. Each bandwidth of EEG signals represents a particular mental state [21]. Several studies demonstrated, for example, the correlation between the EEG Power Spectrum Density (PSD) variation and the subjects' responses when exposed to different ambient temperatures. They reported that different temperatures correspond to modulation of power in particular brain frequency bands. For example, Yao et al. [22] compared brain frequency bands of subjects exposed to low, neutral, and high temperatures, finding that the beta band was

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significantly higher in cold and warm states compared with the neutral condition. Lv and colleagues [23] demonstrated a higher value of the delta band in the warm condition compared with the neutral one. Although the studies based on the calculation of the PSD give results relating to the thermal condition of the subjects, these often appear to be in disagreement. In addition, none of these unambiguously identifies the thermal state of the subject. In this view, we proposed a novel methodological approach based on a combination of the usage of wearable sensor for EEG data recording and a novel method of EEG data analysis based on the calculation of entropy. The concept of entropy was introduced by Clausius [24] in the field of thermodynamics at the end of the 19th century. Later, Shannon [25] applied this concept to information theory, proposing its application in a wide range of information science fields. The human brain, as a dynamic complex system, can be studied with entropy (non-linear method) to quantify the complexity of brain areas' changes [26] . Different types of entropy are available to quantify the complexity of EEG signals, such as Approximate Entropy (ApEn) [27], Sample Entropy (SamEn) [28], and MultiScale Entropy (MSE) [29]. In the current study, ApEn was selected for the analysis, due to its properties: good reproducibility to time series of at least 50 data points; low-noise, and reliability for both stochastic processes and noisy deterministic systems [30]. The calculation of ApEn is not based on the underlying distribution of the data; instead, it measures the predictability of future amplitude values of time series using the knowledge of the general one or two previous amplitude values, leading to the possibility to apply this approach to signals of short length without the necessity to make the model estimation [31]. Despite entropy being used in the analysis of EEG signals in many fields of application [32–34], it represents a novel approach applied to the analysis if EEG signal to assess thermal states differences of a building's occupants. This study explores brain responses applying ApEn measure for assessing thermal sensation differences of subjects exposed to three predetermined ambient temperatures, a representative for cold (18℃), neutral (24 ℃), and warm (33℃) environments. A 4-channels wearable EEG was used for signal acquisition.

2 Materials and Methods

2.1 Experimental equipment and environment

The experimental sessions were carried out in the NEXT.ROOM [35,36], a human multidomain comfort test room built at the Environmental Applied Physic Lab (eplab.net) at the University of Perugia (Italy). It is a laboratory facility of 4x4x2.7 m^3 where a set of environmental sensors allow to monitor and control of the parameters listed in Table 1 [37].

Table 1. Technical specification of the installed environmental sensors in the NEXT.ROOM.

Measured Parameters	Technical specification	Position
Air temperature	Accuracy: ± 0.1 °C	Height: 0.10/0.60/1.10/ 1.60 m
Relative humidity	Accuracy: ± 1.5%	Height: 1.10 m
Air velocity	Accuracy: ± 0.2 m/s	Height: 1.10 m
CO_2 Concentration	Accuracy: ± 50 ppm	Height: 1.10 m
Illuminance	Range: 20÷ 2000 lx	On the desk surface

2.2 EEG measurements device

A brain sensing headband Muse 2 (Interexon Inc.) [38] was used for electroencephalographic measurements. Researchers provided evidence that Muse is an effective portable tool for continuous recording EEG data [39,40], applicable also outside of its designed functionality (meditation and training device). In the field of thermal comfort evaluation, the authors validated the usage of this portable device for EEG measurements, assessing its capabilities to discriminate different human thermal sensation and its low invasiveness for the participants, during experimental session [41,42]. The EEG signals were obtained from 4 input electrodes. The two input electrodes are on the forehead (left and right of the reference: AF7, AF8, silver made) identifying the anterior frontal site and one input electrode above each ear (TP9 and TP10, conductive silicone -rubber), identifying the temporoparietal site. Three reference electrodes (FPz - CMS/DRL) are placed in the middle between the two input electrodes on the forehead, Fig. 1. The Muse 2-Bundle does not require the application of a conductive gel; however, the skin of the forehead and mastoids were dampened to enhance electrical conductance. EEG data were recorded using the Muse application [43] paired with a smartphone via Bluetooth low Energy (BLE) at 256 Hz sampling frequency.

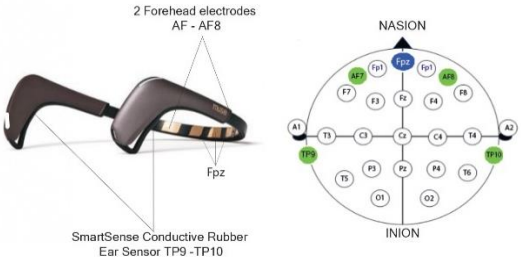

Fig. 1. Left: MUSE 2 sensors overview. Right: Top-down view of the EEG electrode positions on the subject's head.

2.3 Experimental procedure

Twenty-four healthy volunteers, 10 females and 14 males (age 24 ± 1.8), were enrolled in the experimental

campaign. The three test sessions were conducted in May 2022. The average clothing thermal insulation was 0.6 clo, typical for springtime. The metabolic rate of the participant was 1.1 met according to standards ISO 7730 [44]. Each subject took part in the experiment individually, Fig. 2. All the participants were invited to not smoke, perform physical activity, and not eat or drink anything at least one hour before their test, to avoid the metabolic process alteration. Subjects were asked to sit down and keep relaxed; no activity was allowed to reduce artifact movements in the physiological measurements.

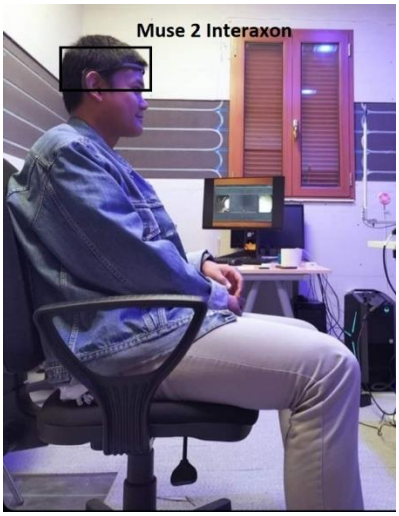

Fig. 2. Measurements of EEG signals with headband Muse 2 (Interexon Inc.) in the NEXT.ROOM.

The three experimental sessions were designed to reproduce the same environmental conditions in terms of relative humidity, air velocity, CO2 concentration, and illuminance level, which were kept constant, while the air temperature was set at the operative value recognized for thermally cold, neutral, and warm environment, according with ISO 7730:2005 [8]. Table 2. reports the mean and the standard deviation (SD) of each environmental parameter monitored during each test using data logging system [37].

Table 2. Mean values and SD of the environmental monitored parameters during experimental sessions.

Measured Parameters	Cold	Neutral	Warm
Air temperature [°C]	16.1 ± 0.4	25.2 ± 0.3	33.4 ± 0.5
Relative humidity [%]	26.1 ± 0.5	21.2 ± 0.3	17.9 ± 0.3
Air velocity [m/s]	0.1 ± 0.03	0.08 ± 0.02	0.07 ± 0.04
CO_2 Concentration [ppm]	485 ± 9	493 ± 5	503 ± 7
Illuminance [lx]	500 ± 22	498 ± 25	502 ± 23

The tests were scheduled from 9:00 a.m. to 1:00 p.m. and from 3:00 p.m. to 6:00 p.m. Each test lasts 20 min, 15 min for thermal adaptation (according to the literature [45]), and 5 for data recording. Before starting the subjects were informed about the aim of the project, and they were asked to sign an informed consent for personal data management. At the end of each session, they filled out a second questionnaire to provide their responses about the environmental perception in terms of thermal sensation using a score based on a Likert 5-point scale where 0 represents the neutrality.

2.4 EEG data processing

2.4.1 EEG data cleaning

The data were processed using a processing custom code was implemented in MATLAB software, based on EEGLAB toolbox codes[46,47]. EEG data were band-pass filtered using a finite impulse filter (FIR) to extract data in the frequency range from 0.2 to 47 Hz [48]. EEG continuous data were segmented in 2 seconds length epochs and trials with artifact activity (such as scalp muscle activity and cardiac activity) or aberrant waveforms were removed by an expert data visual inspection [49]. After this inspection, about 4 minutes of EEG data remained for each session. Fig. 3. shows EEG data of a single subject before and after pre-processing data cleaning.

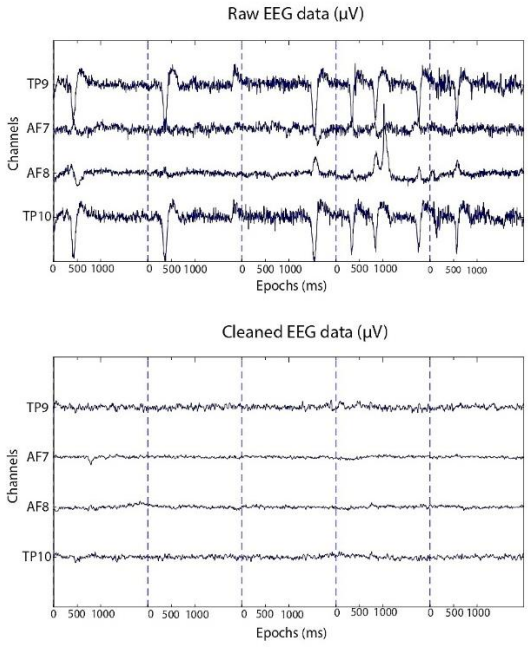

Fig. 3. Raw EEG data of subject 101 in warm condition, before pre-processing. Cleaned EEG data of subject 101 in warm condition, after pre-processing.

2.4.2 EEG Entropy

The complexity of brain activity was studied by entropy measure evaluated by Approximate Entropy (ApEn) [50,51]. These values were computed, for each

participant and for each channel in the Total Spectrum (0.2-47 Hz) using a processing custom code implemented in MATLAB software. Firstly, a value of ApEn was computed for each channel and each epoch, then, those values were averaged among the epochs to obtain a single ApEn value for each channel. The software estimates ApEn dimensionless values. The higher the value of ApEn, the more irregular and less predictable the signal is. On the other hand, the lower this value, the more periodic and stable the signal tends to be [52,53]. The obtained ApEn values range from 0 (regular time series) to 2 (random time series). In the ApEn analysis two input parameters need to be defined: a model length *m* and a tolerance factor *r*, also called similarity factor, used to identify a range of similarities between data points. In this study, *m* and *r* were set equal to the default MATLAB values: thus, *m = 2* and *r = 0.2 * variance (x)* [54] were used, in which *x* corresponds to an epoch of length of 2 seconds of a specific channel. [55]

In particular, the calculation of ApEn is described as follows [56]:

1. A point-by-point comparison is made between each data sequence of a model length *m* and all other sequences. If the distance between points is less than the tolerance factor *r* a match is scored.
   All the matches are counted as described by the expression (1)

$$N_i = \sum_{i=1, i\neq k}^{N} (\|Y_i - Y_k\|_\infty < r) \quad (1)$$

   where Y_i is the m-dimensional vector sequence, defined as a delayed reconstruction of the time series $\{y(i)\} = y(1)\ , y(2), \dots, y(N)$, where i ranges from 1 to *N,* number of data points:

$$Y_i = [y(i), y(i+1), \dots, y(i+m+1)] \quad (2)$$

2. The comparison is performed on each successive *m+1*-long sequence, starting form the first sequence of *m+1* points, as shown in the equation (2).
3. The number of matches is converted to a natural logarithm value, and afterwards normalized by the number of data points (*N*):

$$\phi_m = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \log(N_i) \quad (3)$$

   Finally, the ApEn is calculated using the following expression:

$$ApEn = \phi_m - \phi_{m+1} \quad (4)$$

2.4.3 Statistical analysis

A statistical Analysis of Variance (ANOVA) design between three factors, Temperature (cold, neutral, warm), Site (anterior frontal, temporoparietal), and Side (Left, Right) was used to evaluate the statistical differences in terms of ApEn values between the three thermal conditions, with a statistical cut-off level of $p<0.05$. ANOVA was implemented with the software Statistica (StatSoft Inc.). The normality of the data was tested using the Kolmogorov-Smirnov test, and the hypothesis of Gaussianity could not be rejected. ANOVA was chosen since it is known to be robust for the departure of normality and homoscedasticity of data being treated. Greenhouse and Geisser correction was used for the protection against the violation of the sphericity assumption in the repeated measure ANOVA. Moreover, the post-hoc analysis was performed using Duncan's test and a 0.05 significance level.

3 Results

The ANOVA for the evaluation of the ApEn index showed a statistically significant main effect ($F(1, 23) = 21.037$, $p=0.00013$) for the factor Site (temporoparietal, Anterior frontal) demonstrating as the temporoparietal site exhibited lower values of entropy regardless the temperature condition. Furthermore, the ANOVA also showed a significant interaction ($F(2,46) = 3.8170$, $p= 0.02926$) between the factors' temperatures (cold, neutral, warm) and Site (anterior frontal, temporoparietal). As shown in Fig. 4., in both sites, the neutral temperature condition presented higher values of ApEn for the cold and warm ones, as well as every variation from the thermal neutrality, reflecting lower entropy in the EEG signals. In particular, the Duncan post hoc analysis revealed as, in the temporoparietal area, the neutral condition presented higher entropy compared to the cold condition ($p=0.00019$) and the warm one ($p=0.00348$). Likewise, in the anterior frontal area, the neutral condition exhibits higher entropy compared to the cold ($p= 0.02417$) and warm ($p=0.00007$) ones. Additionally, while cold and warm temperatures elicited similar entropy values in the temporoparietal site, in the anterior frontal area, it is notable a trend of ApEn with gradually smaller values from the neutral to the Warm condition, with the cold one that results intermediate (neutral > cold > warm). The cold condition presented less entropy compared to the neutral one ($p= 0.02417$) as mentioned above, but more entropy ($p= 0.00952$) compared to the warm one.

Table 3. Approximate Entropy values in terms of Mean and Standard Error (Mean ± SE) between subjects for each thermal condition (cold, neutral, warm) and each brain region (anterior frontal, temporoparietal).

Brain Regions	Cold	Neutral	Warm
Anterior frontal	0.719 ± 0.026	0.78 ± 0.027	0.736 ± 0.022
Temporoparietal	0.836 ± 0.020	0.869 ± 0.026	0.798 ± 0.028

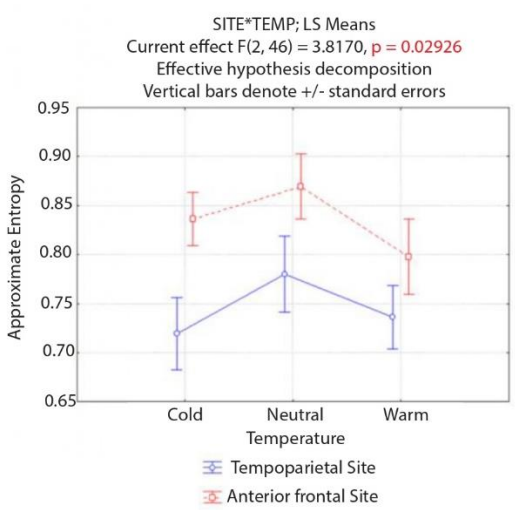

Fig. 4. ANOVA significant interaction (F (2,46) = 3.8170, p= 0.02926) of Approximate Entropy values among the factors' temperatures (cold, neutral, warm) and Site (anterior frontal, tmporoparietal). The Duncan post hoc analysis revealed as, in the temporoparietal site, the neutral condition presented higher entropy compared to cold condition (p=0.00019) and to the warm one (p=0.00348). Likewise, in the anterior frontal site, the neutral temperature exhibits higher entropy compared to the cold (p= 0.02417) and warm (p=0.00007) ones.

4 Discussion

The presented research proposed a novel EEG data analysis approach based on the calculation of EEG Entropy aimed at identifying differences between human thermal conditions. An experimental campaign was designed and conducted in a controlled environment to expose twenty-four subjects to three ambient temperatures, a representative of the thermally cold, neutral, and warm scenario. EEG data were recorded using a wearable device. Results confirmed previous research findings in the application of wearable sensors, highlighting that they are a promising solution for providing reliable data for thermal comfort investigation. In particular, for both anterior frontal and temporoparietal sites there were significant differences between neutral, and cold, and warm conditions, showing a higher value of ApEn in the neutral condition with respect to the other ones. In an oversimplification of how the brain may work, we can imagine the brain's neural population as a system that persists in a sort of firing baseline state, that in response to a stimulus can deviate from this state to a different firing state that may give rise to a less complex system (more regular firing pattern) or to a more complex one (neural activity is more random). In this sense, we could hypothesize that the low randomness values of the revealed electrical activity in specific thermal conditions are the results of the subjects' thermal changes from the baseline of the neutral temperature. Additionally, it is important to highlight that, while cold and warm temperatures elicited similar entropy values in the temporoparietal site, in the anterior frontal area, it is notable a significative trend of ApEn index with gradually smaller values from the neutral to the warm condition, with the cold intermediate (neutral > cold > warm). In this sense, the anterior frontal region seems to be more sensitive to thermal changes, distinguishing the single temperature conditions, at least in terms of entropy values. Few neuroimaging research have shown different activation of brain areas associated with different thermal sensations (discriminative rating process) [57]. Among the brain areas more active in thermal rating processes the anterior cingulate cortex (ACC) in the prefrontal cortex seems to be the highest active including other regions such as the medial prefrontal cortex, and the orbitofrontal cortex in the frontal lobe. In this view, we can speculate that the frontal area can be one of the best candidates involved in the discriminative thermal processes. Although deeper research is necessary, the measurement of entropy can represent a potential approach for studying brain response to thermal stimuli.

5 Conclusion

The present is the first study that experimentally demonstrate the applicability of a novel data analysis approach for EEG measurements based on the entropy index, aimed at discriminating human thermal conditions. Further analysis is necessary to validate these methods and to evaluate different environmental conditions, where other factors (light, noise, air quality) can alter the human thermal perception. In general, entropy analysis seems to provide an additional instrument for improving the existing physiological interpretation of human thermal response, having the potential to give support and robustness to the actual personalized thermal comfort models.

Acknowledgment

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