Feature Extraction for Emotion Recognition and Modelling using Neurophysiological Data

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***Abstract*—The ubiquitous computing paradigm is becoming a reality; we are reaching a level of automation and computing in which people and devices interact seamlessly. However, one of the main challenges is the difficulty users have in interacting with these increasingly complex systems. Ultimately, endowing machines with the ability to perceive users emotions will enable a more intuitive and reliable interaction. Consequently, using the electroencephalogram (EEG) as a bio-signal sensor, the affective state of a user can be modelled and subsequently utilised in order to achieve a system that can recognise and react to the users emotions. In this context, this paper investigates feature vector generation from EEG signals for the purpose of affective state modelling based on Russells Circumplex Model. Investigations are presented that aim to provide the foundation for future work in modelling user affect and interaction experiences through exploitation of different input modalities. The DEAP dataset was used within this work, along with a Support Vector Machine, which yielded reasonable classification accuracies for *Valence* and *Arousal* using feature vectors based on statistical measurements and band power from the α, β, δ, and θ waves and High Order Crossing of the EEG signal.**

1. Introduction

In the context of intelligent systems, we are facing a paradigm shift: from a world where users control devices to a world of autonomous devices, capable of self-management and aware of their environmental and situational context [1]. Ubiquitous computing as envisioned by Mark Weiser is becoming a reality; we are reaching a level of automation and computing in which people and devices interact seamlessly, without this interaction being perceived by the user [2].

Ironically, one of the main challenges found in this paradigm is the difficulty of user interacting with these systems due to their increasing complexity [3]. Consequently, it is important to identify all possible interaction modalities and structure these based on the requirements of the problem domain, which may include both traditional and natural user interfaces, situational awareness and adaptation, personalised content management, multimodal dialogue and multimedia applications. Moreover, the computer mediated nature of interaction modalities such as Virtual Reality typically requires a facility for personalised interaction in order to maintain user engagement with the underlying task. While task engagement encompasses both the user's cognitive activity and motivation, it also requires an understanding of affective change in the user. Accordingly, physiological computing systems may be utilised to provide insight into the cognitive and affective processes associated with task engagement [4]. In particular, an indication of the levels of brain activity, through acquisition and processing of electroencephalogram (EEG) signals, may yield benefits when incorporated as an additional input modality [5]. In recent studies, researches have used Brain-Computer Interface (BCI) systems in order to match the responses of the environment directly to the user's brain activity [6], [7], [8], [9], [10].

Currently, Human-Computer Interaction (HCI) research targets the use of BCI systems as a novel input modality, typically for control purposes, enhancing traditional modalities such as mouse, keyboard, or game controller. Subsequently, beyond assistive technology applications, today BCI technology is considered as another potential input modality. However, this form of active interaction is still quite costly for users as it requires training and a good amount of both concentration and effort to modulate ones brain activity, which ultimately causes the user to focus more on the interaction modality itself than the underlying task. In order to achieve truly transparent interaction, the system is required to acquiesce to the users intentions or needs. Consequently, using the EEG as a bio-signal sensor to model the users cognitive and affective state is one potential way to achieve an interaction that does not require any training or attention focus from the user. Focusing on the users affective state, this paper investigates different feature extraction techniques in order to relate and discover useful patterns between EEG signals and their respective levels of *Valence* and *Arousal*. For the purposes of the investigations, the DEAP dataset has been utilised to provide an annotated set of EEG signals [11], and Support Vector Machine (SVM) employed to generate an affective state model.

The structure of the remainder of this paper is as follows: Section 2 provides a brief overview of approaches to affect-based modelling within the existing literature; Section 3 describes both the dataset and underlying methodology employed within the investigations carried out, with the corresponding set of results presented in Section 4. This is subsequently followed by a discussion of the results in Section 5. Finally, Section 6 provides an indication of general heuristics gained from the observations made, along with aspects for consideration in future works.

2. Background

Providing machines with the ability to recognise and detect the emotional states of users could be of major importance for the next generation user interfaces. Endowing computer systems with logical reasoning abilities about the users affective context will facilitate detection and recognition of the affective states they are currently experiencing, especially indications of frustration, fear, or dislike, and enable the system to respond in a more empathetic and intelligent manner [12]. As a consequence, this together with other HCI characteristics such as consistency, flexibility, usability, and accessibility may provide a catalyst for the production of intelligent and adaptive interfaces [13].

Currently, various input modalities exist that can be utilised to acquire information about the user, which can be exploited for the purpose of recognising emotion. Firstly, audiovisual-based communication, such as eye gaze tracking, facial expressions, body movement detection, and speech and auditory analysis may be employed as input modalities. Secondly, physiological measurements using sensor-based input signals, such as EEG, galvanic skin response, and electrocardiogram can also be utilised. However, the use of EEG as an input modality has a number of advantages that make it potentially suitable for use in real-life tasks including its non-invasive nature and relative tolerance to movement. Additionally, EEG can work on a very high level for temporal resolution [14].

Accordingly, several existing studies have exploited EEG as an input modality for the purpose of emotion recognition. For instance, Picard *et al.* looked at different techniques for feature extraction and selection in order to enhance emotion recognition by employing EEG data in conjunction with various transformations [15]. And they found that there is a variation in physiological signals of the same subject expressing the same emotion from day to day. Which impairs recognition accuracy if not managed properly. Konstantinidis *et al.* studied real-time classification of emotions by analysing EEG data recorded using 19 channels. They showed that extracting features from EEG data using a complex non-linear computation, which is a multi-channel correlation dimension, and processing the features using a parallel computing platform (i.e. CUDA) would substantially reduce the processing time needed, hence facilitate real-time emotion recognition [16]. In [17], emotion recognition from EEG as proposed using feature extraction methods based on Higher Order Crossing (HOC) analysis, in which the features represent the oscillatory patterns exist in the EEG data. Additionally, they used four different classification techniques on HOC features extracted from each channel separately, as well as HOC features extracted from data combining four channels together. Furthermore, they reported the highest classification accuracy achieved 83.33%, using SVM trained on extracted HOC features. Murugappan investigated feature extraction using wavelet transforms [18]. Moreover, he used K-Nearest Neighbor to evaluate classification accuracy for emotions across two different sets of EEG channels (24 and 64 channels), with a resulting classification accuracy of 82.87%. Jenke *et al.* looked for feature selection methods of features extracted from EEG for emotion recognition [19]. They presented a systematic comparison that concluded multi-variate methods perform better than uni-variate methods for feature selection in this context.

Nevertheless, still there are challenges that may be encountered when attempting to exploit EEG for emotional state recognition. For example, due to the poor signal-to-noise ratio associated with the EEG signal, a number of constraints must be applied and per subject analysis performed. Therefore, extracting relevant and informative features from EEG signals from a large number of subjects and formulating a suitable representation of this data in order to distinguish different affective states is an extremely complicated process [20].

3. Methodology

As previously discussed, the ever growing ubiquity of computer systems deployed within our everyday lives necessitates further system awareness of the emotional state of the user. In order to investigate EEG signal feature selection, for subsequent affective state modelling, an existing dataset was used. The following subsections describe the dataset, feature extraction approaches, and analysis method employed for the purposes of emotion recognition and modelling using neurophysiological data.

3.1. The DEAP Dataset

The DEAP dataset [11], utilised in the work presented herein, comprises EEG and peripheral physiological signals for 32 subjects who individually watched 40 one-minute music videos of different genres as a stimulus to induce different affective and emotional states. Within the dataset 32 channels were used to record EEG signals for each trial per subject, resulting in 8064 samples that represent the signal over each one-minute trial. During each trial, a single subject rated his/her feelings after watching the video using the Self Assessment Manikin (SAM) scale in the range [1-9] to indicate the associated levels of *Valence*, *Arousal*, *Dominance*, and *Liking*.

Furthermore, the resulting EEG signal data averaged to the common reference, the EEG channels were reordered to follow the Geneva order, and finally, the data segmented

TABLE 1. EEG BRAIN WAVE BANDS

Band Name	Band Symbol	Frequency Range (HZ)
Delta	δ	0.5 - 4
Theta	θ	4 - 8
Alpha	α	8 - 12
Beta	β	12 - 30

into 60 second trials and a three second pre-trial baseline was removed.

3.2. Bandwave Extraction

The investigations exploited the four primary channels Fp1, Fp2, F3 and F4 that are relevant to the detection and analysis of affective states, according to [17]. Furthermore, the EEG data associated with these channels was transformed into α, β, δ, and θ waves, using the ParksMcClellan algorithm and Chebyshev Finite Impulse Response filter to filter the signal according to the ranges shown in Table 1.

3.3. Feature Extraction

Three feature extraction techniques for EEG-based emotion recognition were implemented and applied to the acquired signals.

3.3.1. Statistical Features. We have initially adopted six descriptive statistics, as suggested by Picard *et al.* in [15]:

1) Mean (μ)

$$\frac{1}{N}\sum_{n=1}^{N} X_n$$

2) Standard deviation (σ)

$$\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(X_n - Mean)^2}$$

3) Mean of the absolute values of the first differences *(AFD)*

$$\frac{1}{N-1}\sum_{n=1}^{N-1}|X_{n+1} - X_n|$$

4) Mean of the normalised absolute values of the first differences *(AFDN)*

$$\frac{1}{N-1}\sum_{n=1}^{N-1}|\tilde{X}_{n+1} - \tilde{X}_n|$$

5) Mean of the absolute values of the second differences *(ASD)*

$$\frac{1}{N-2}\sum_{n=1}^{N-2}|X_{n+2} - X_n|$$

6) Mean of the normalised absolute values of the second differences *(ASDN)*

$$\frac{1}{N-2}\sum_{n=1}^{N-2}|\tilde{X}_{n+2} - \tilde{X}_n|$$

3.3.2. Spectral Power Density of Brain Waves. For the selected four channels, the mean log-transformed brain wave power were extracted from the α, β, δ, and θ frequency bands, according to [21]. The Spectral Power Density (SPD) is widely used to detect the activity level in each brain wave, allowing the components in the frequency domain to be interpreted as electroencephalographic rhythms. Subsequently, the power features resulting from the four channels, for each of the four frequency bands, were combined together prior to subsequent analysis.

3.3.3. Higher Order Crossing. In this technique, the EEG signal is interpreted as a finite time series. It is possible to characterise a finite series (Zt, such that t = 1, ..., N) oscillating through the zero point by the number of intersections, or crossings, for this level. Such a number of crossings can be changed by applying a filter to adjust the oscillation of the series. From this perspective it is possible to assume the filtering-counting process by applying a filter to the series and performing a count of the zero crossings [22] [23], resulting in a high order crossing after applying a specific sequence of filters.

Considering the difference operator ($\bigtriangledown$), defined as $\bigtriangledown Z_t \equiv Z_t - Z_{t-1}$, as a high-pass filter. We can consider a sequence of filters such as $\Im_1 \equiv \bigtriangledown_{k-1}$, with $k = 1, 2, 3, ...$ and can estimate the sequence of HOC crosses as:

$$D_k = NCZ\left\{\Im_k\left(Z_t\right)\right\}, k = 1, 2, 3, ...; t = 1, ..., N$$

Being $NCZ\{\}$ the number of zero-crosses for each filter, in which:

$$\Im\left(Z_t\right) = \bigtriangledown^{k-1} Z_t = \sum_{j=1}^{k} \binom{k-1}{j-1} \left(-1\right)^{j-1} Z_{t-j+1}$$

To calculate the number of zero-crossings, a binary time series is initially constructed given by:

$$X_t\left(k\right) = \begin{cases} 1, & \Im_k\left(Z_t\right) \geq 0 \\ 0, & \Im_k\left(Z_t\right) < 0 \end{cases}, k = 1, 2, 3, ...; t = 1, ...N$$

And finally the HOC is estimated by:

$$D_k = \sum_{t=2}^{N} \left[X_t\left(k\right) - X_{t-1}\left(k\right)\right]^2$$

3.4. Affective State Classification Methods

The Circumplex Model of emotion developed by James Russell suggests that the core of emotional states are distributed in a two-dimensional circular space, containing *Arousal* and *Valence* dimensions. *Arousal* represents the vertical axis and *Valence* represents the horizontal axis, while the center of the circle represents a neutral *Valence* and a medium level of *Arousal* [24].

As the current study is interested in recognising the affective state that a subject is experiencing, congruous with Russells Circumplex Model, throughout the investigations only *Valence* and *Arousal* ratings were used. Furthermore, ratings are provided within the DEAP dataset as continuum

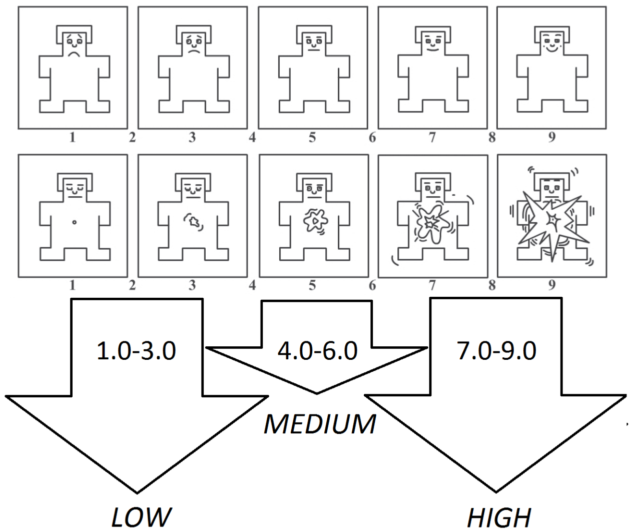

Figure 1. Mapping from SAM scale value ranges to Tripartition Scheme Labels (*Low*, *Medium*, *High*)

numeric values ranging from [1-9] based on the SAM scale [25]. Subsequently, two different partitioning schemes have been employed in order to discretize the range of values within the scale, as illustrated in Figure 1, and given as follows:

1) *Tripartition Labeling Scheme*: Dividing the scale into three ranges [1.0-3.0], [4.0-6.0] and [7.0-9.0], given as the partitions *Low, Medium* and *High* respectively.
2) *Bipartition Labeling Scheme*: Similar to the previous scheme, however we removed instances annotated as *Medium*, resulting in the two ranges [1.0-3.0] and [7.0-9.0], given as the partitions *Low* and *High* respectively.

Within the research literature, a range of classification techniques have been used for affective computing and emotion recognition using EEG bio-signals as an input modality [26]. In this work, we employ a Support Vector Machine (SVM), specifically the C-Support Vector with a linear kernel, available from the LIBSVM library developed at National Taiwan University [27], [28].

4. Experimental Results

For the sake of exploration of different features, as previously described, we used classification accuracy as a metric. Furthermore, we have utilised the 10-fold cross validation approach for assessing classification performance. As previously discussed, this investigation aims to identify patterns related to data extracted from EEG bio-signals across different *Valence* and *Arousal* states. Subsequently, feature vectors for the SVM classifier utilised a range of statistics-based measures; in some cases the feature vector comprised individual statistical values, whereas in other cases the feature vector comprised a concatenation of statistical values. Moreover, two labeling schemes were employed during the investigations, i.e. *Bipartition* and *Tripartition*.

TABLE 2. CLASSIFICATION ACCURACIES USING STATISTICS-BASED FEATURE VECTORS DERIVED FROM PREPROCESSED EEG SIGNALS

Method	Features #	Valence	Arousal	Average	Scheme
μ	32	49.22%	55.23%	52.23%	Tripartition
μ	32	64.32%	64.77%	64.54%	Bipartition
σ	32	52.81%	56.41%	54.61%	Tripartition
σ	32	71.33%	63.49%	67.41%	Bipartition
AFD	32	54.69%	56.09%	55.39%	Tripartition
AFD	32	74.53%	67.55%	71.04%	Bipartition
AFDN	32	51.72%	55.16%	53.44%	Tripartition
AFDN	32	69.71%	68.15%	68.93%	Bipartition
μ , σ	64	51.80%	55.47%	53.63%	Tripartition
μ , σ	64	69.58%	65.16%	67.37%	Bipartition
All	128	52.89%	54.06%	53.48%	Tripartition
All	128	69.77%	66.09%	67.93%	Bipartition

TABLE 3. CLASSIFICATION ACCURACIES USING STATISTICS-BASED FEATURE VECTOR DERIVED FROM α, β, δ AND θ WAVES

Features #	Valence	Arousal	Average	Scheme
96	58.75%	58.75%	58.75%	Tripartition
96	85.99%	73.67%	79.83%	Bipartition

Table 2 provides the classification accuracies obtained from the use of statistical measures as feature vectors for the classifier. As may be observed in Table 2, the statistical features μ, σ, *AFS* and *AFDN* were tested individually. In addition, the statistical features μ and σ were concatenated, producing an additional feature vector. Lastly, all four statistical features (μ, σ, *AFS* and *AFDN*) were concatenated together to produce another feature vector. It was discovered that *AFD* achieves the highest accuracy when classifying *Valence* (74.53%), along with the highest mean accuracy (71.04%), yet a marginal improvement can be observed in the use of *AFDN*, which classifies *Arousal* with an accuracy of 68.15%. However, the *Bipartition* mapping scheme outperforms the *Tripartition* scheme regardless of the choice of feature vector.

In a similar manner, Table 3 gives the results for the classification accuracies obtained when using all statistical features (i.e. μ, σ, *AFD*, *AFDN*, *ASD* and *ASDN*) derived from the α, β, δ and θ waves for each of the selected channels. Consequently, the results in Table 3 show classification accuracy of 85.99% and 73.83% for *Valence* and *Arousal* respectively when using the *Bipartition* mapping scheme.

In addition to the previous results, Table 4 gives the classification accuracies obtained when exploiting the power bands of the the α, β, δ and θ waves as features for each channel. Subsequently, best performance is again shown when using the *Bipartition* mapping scheme, thereby achieving classification accuracies of 82.53% and 76.89% for *Valence* and *Arousal* respectively.

Table 5 provides the classification accuracies obtained when utilising feature vectors generated using the HOC statistics from each channel. Similar to the previous results,

TABLE 4. CLASSIFICATION ACCURACIES USING A POWER DENSITY-BASED FEATURE VECTOR DERIVED FROM α, β, δ AND θ WAVES

Features #	Valence	Arousal	Average	Scheme
16	59.77%	61.09%	60.43%	Tripartition
16	82.53%	71.25%	76.89%	Bipartition

TABLE 5. CLASSIFICATION ACCURACIES USING HOC-BASED FEATURE VECTOR

Features #	Valence	Arousal	Average	Scheme
24	53.83%	55.86%	54.84%	Tripartition
24	66.9%	66.69%	66.8%	Bipartition

Table 5 shows the best classification accuracies (i.e. 66.90% for *Valence* and 66.69% for *Arousal*) were achieved when the *Bipartition* mapping scheme was employed.

An additional endeavour carried out during the investigations was to probe the relationship between the emotional states reported by the subjects and the actual power bands of the measured EEG signals. Consequently, by averaging the power bands of the α, β, δ and θ waves from the four channels across all 32 subjects over the *Valence* and *Arousal* states, an insight into the relationship may be determined. As Figure 2 indicates, there appears to exist an inversely proportional relationship between *Valence* and the power band features. In contrast, in the case of *Arousal*, no distinct relationship can be observed.

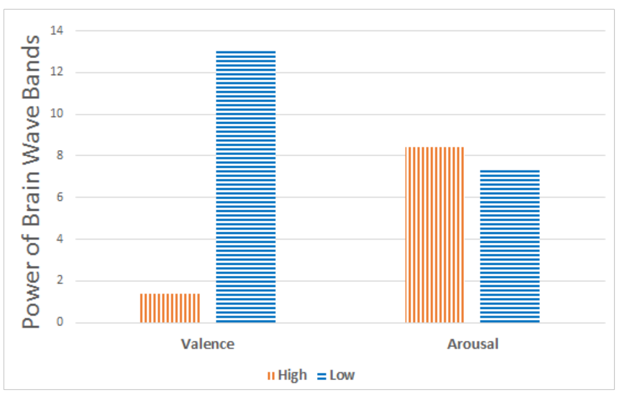

Figure 2. Comparison of Average Power Bands with Bipartition-based *Valence* and *Arousal* Selection

5. Discussion

The investigations and associated results presented in this paper show the potential of utilizing EEG signal data with the intention of recognising and modelling the affective states of a user. In particular, the highest classification accuracy rates obtained used a feature vector generated from features based on the statistical measurements derived from the α, β, δ and θ waves, e.g 85.99% for *Valence* and 73.83% for *Arousal*. Likewise, using a feature vector based on the associated power bands also produced a reasonable degree of classification accuracy, e.g. 82.53% for *Valence* and 76.89% for *Arousal*. In both cases, the *Bipartition* labeling scheme was used. Furthermore, in the majority of the investigations, the classification accuracies obtained for *Valence* outperformed those obtained for *Arousal*.

However, the variance observed amongst the results obtained from the investigations could be due to many reasons. Firstly, the sensitivity of the self-assessment scale used to garner affect ratings; this kind of measurement is somewhat subjective, as it is based on the thoughts and impressions of the participant about the video he/she watched. Moreover, it is often the case that people do not know how to articulate their actual emotions and associated states due to ambiguity and mixed mental activities [29]. Therefore, it is potentially the case that some of the participants could not precisely entail their actual emotional state using the SAM scale. Due to this factor, classification models were generated twice using two different mapping schemes in order to determine the impact from ambiguous annotations that potentially arise from the selection of *Valence* and *Arousal* values from the middle of the self-assessment scale. As the results indicated, placing such a constraint on the ranges of affect to be modelled improved the overall classification performance. Secondly, it is common that people intermix and are unable to differentiate between *Valence* and *Arousal* states. In particular, participants within the DEAP dataset watched video clips as a stimuli, hence were passive during that time. Therefore, it is probable that self-assessing the *Arousal* state was somewhat vague, which would explain the lower accuracy rates achieved for the state.

Moreover, combining extracted features together to form a feature vector does not necessarily correspond to an increase in the classification accuracy. For example, as shown in Table 2, Absolute First Difference *(AFD)* of the preprocessed EEG signals achieves a better classification accuracy than other individual features as well as collectively combined features. Additionally, as Figure 2 depicts, a direct relationship was observed between the power bands of the α, β, δ and θ waves and the classification accuracies obtained for *Valence*. Therefore, the ease with which this pattern may be observed makes it potentially suited as a metric for measuring this aspect of the affective state of a user, ranging from negative to positive (i.e. *Low-Valence* to *High-Valence*).

6. Conclusion and Future Work

This paper investigated exploiting electroencephalogram data for the purpose of recognising and modelling the affective states of users. Consequently, the results from several experiments using different sets of features extracted from EEG data within the DEAP dataset were presented. In addition, the observed discrepancy in classification accuracy due to different affective state mapping schemes was discussed, indicating that a degree of ambiguity will exist within such datasets, which has an obvious effect on the ability to accurately model affective states. These preliminary results will help inform and lead to further experiments that eventually integrate different input modalities together with EEG in order to potentially provide a more robust model of the users affective state. As a next step, the current set of investigations will be repeated using another mapping scheme based on Fuzzy Logic in an effort to improve the classification of potentially ambiguous affective states.

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References

[1] W. S. Ark, "A systematic approach to occupancy modeling in ambient sensor-rich buildings," *IBM Systems Journal*, vol. 38, no. 4, pp. 504–507, 1999.

[2] M. Weiser, "The computer for the 21st century," *Scientific American*, vol. 256, pp. 94–104, 1991.

[3] M. Pantic, A. Nijholt, A. Pentland, and T. S. Huanag, "Human-centred intelligent human? computer interaction (hci): how far are we from attaining it?" *International Journal of Autonomous and Adaptive Communications Systems*, vol. 1, no. 2, pp. 168–187, 2008.

[4] S. H. Fairclough, K. Gilleade, K. C. Ewing, and J. Roberts, "Capturing user engagement via psychophysiology: Measures and mechanisms for biocybernetic adaptation," *Int. J. Auton. Adapt. Commun. Syst.*, vol. 6, no. 1, pp. 63–79, Dec. 2013. [Online]. Available: http://dx.doi.org/10.1504/IJAACS.2013.050694

[5] D. Szafir and B. Mutlu, "Pay attention!: Designing adaptive agents that monitor and improve user engagement," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ser. CHI '12. New York, NY, USA: ACM, 2012, pp. 11–20. [Online]. Available: http://doi.acm.org/10.1145/2207676.2207679

[6] J. R. Wolpaw, "Brain-computer interfaces: Progress, problems, and possibilities," in *Proceedings of the 2Nd ACM SIGHIT International Health Informatics Symposium*, ser. IHI '12. New York, NY, USA: ACM, 2012, pp. 3–4. [Online]. Available: http://doi.acm.org/10.1145/2110363.2110366

[7] S. B. T. K. G. Ruscher, F. Kruger, "Controlling smart environments using brain computer interface," *Proceedings of the 2nd Workshop on Semantic Models for Adaptive Interactive Systems*, 2011.

[8] L. K. S. Lu, T. Chen, "Eeg-based brain-computer interface for smart living environmental auto-adjustment," *Journal of Medical and Biological Engineering*, 2010.

[9] B. Z. Allison, *Toward Ubiquitous BCIs*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 357–387. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-02091-9_19

[10] A. Nijholt, D. Tan, G. Pfurtscheller, C. Brunner, J. d. R. Millán, B. Allison, B. Graimann, F. Popescu, B. Blankertz, and K.-R. Müller, "Brain-computer interfacing for intelligent systems," *IEEE Intelligent Systems*, vol. 23, no. 3, pp. 72–79, 2008.

[11] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis ;using physiological signals," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 18–31, Jan. 2012. [Online]. Available: http://dx.doi.org/10.1109/T-AFFC.2011.15

[12] R. W. Picard, "Affective computing: challenges," *International Journal of Human-Computer Studies*, vol. 59, no. 1, pp. 55–64, 2003.

[13] A. Dix, J. Finlay, G. D. Abowd, and R. Beale, *Human-Computer Interaction*, 2004, vol. Third. [Online]. Available: http://www.amazon.com/Human-Computer-Interaction-3rd-Alan-Dix/dp/0130461091

[14] B. Burle, L. Spieser, C. Roger, L. Casini, T. Hasbroucq, and F. Vidal, "Spatial and temporal resolutions of eeg: Is it really black and white? a scalp current density view," *International Journal of Psychophysiology*, vol. 97, no. 3, pp. 210 – 220, 2015, on the benefits of using surface Laplacian (current source density) methodology in electrophysiology. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167876015001865

[15] R. W. Picard, E. Vyzas, and J. Healey, "Toward machine emotional intelligence: Analysis of affective physiological state," *IEEE transactions on pattern analysis and machine intelligence*, vol. 23, no. 10, pp. 1175–1191, 2001.

[16] E. I. Konstantinidis, C. A. Frantzidis, C. Pappas, and P. D. Bamidis, "Real time emotion aware applications: A case study employing emotion evocative pictures and neuro-physiological sensing enhanced by graphic processor units," *Computer Methods and Programs in Biomedicine*, vol. 107, no. 1, pp. 16 – 27, 2012, advances in Biomedical Engineering and Computing: the {MEDICON} conference case. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0169260712000831

[17] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from eeg using higher order crossings," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 186–197, 2010.

[18] M. Murugappan, N. Ramachandran, Y. Sazali *et al.*, "Classification of human emotion from eeg using discrete wavelet transform," *Journal of Biomedical Science and Engineering*, vol. 3, no. 04, p. 390, 2010.

[19] R. Jenke, A. Peer, and M. Buss, "Feature extraction and selection for emotion recognition from eeg," *IEEE Transactions on Affective Computing*, vol. 5, no. 3, pp. 327–339, 2014.

[20] A. Schlögl, M. Slater, and G. Pfurtscheller, "Presence research and eeg," in *Proceedings of the 5th International Workshop on Presence*, 2002, pp. 9–11.

[21] R. J. Davidson, "Anterior cerebral asymmetry and the nature of emotion," *Brain and Cognition*, vol. 20, no. 1, pp. 125 – 151, 1992. [Online]. Available: http://www.sciencedirect.com/science/article/pii/027826269290065T

[22] B. Kedem, "Spectral Analysis and Discrimination by Zero-Crossings," *Proc. of the IEEE*, vol. 74, Nov. 1986.

[23] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from eeg using higher order crossings," *Trans. Info. Tech. Biomed.*, vol. 14, no. 2, pp. 186–197, Mar. 2010. [Online]. Available: http://dx.doi.org/10.1109/TITB.2009.2034649

[24] J. A. Russell, "A circumplex model of affect," *Journal of Personality and Social Psychology*, vol. 39, pp. 1161–1178, 1980.

[25] M. M. Bradley and P. J. Lang, "Measuring emotion: the self-assessment manikin and the semantic differential," *Journal of behavior therapy and experimental psychiatry*, vol. 25, no. 1, pp. 49–59, 1994.

[26] M.-K. Kim, M. Kim, E. Oh, and S.-P. Kim, "A review on the computational methods for emotional state estimation from the human eeg," *Computational and mathematical methods in medicine*, vol. 2013, 2013.

[27] C.-C. Chang and C.-J. Lin, "LIBSVM - A Library for Support Vector Machines," 2001. [Online]. Available: http://www.csie.ntu.edu.tw/\ cjlin/libsvm/

[28] Y. EL-Manzalawy, "WLSVM," 2005. [Online]. Available: http://www.cs.iastate.edu/\ yasser/wlsvm/

[29] R. W. Picard, "Affective computing: Challenges," *Int. J. Hum.-Comput. Stud.*, vol. 59, no. 1-2, pp. 55–64, Jul. 2003. [Online]. Available: http://dx.doi.org/10.1016/S1071-5819(03)00052-1