Chen, W. et al. (Eds.) (2017). Proceedings of the 25th International Conference on Computers in Education.
New Zealand: Asia-Pacific Society for Computers in Education

Prospects in Modeling Reader's Affect based on EEG Signals

Kristine KALAW*, Ethel ONG & Judith AZCARRAGA
College of Computer Studies, De La Salle University, Manila, Philippines
*kristine_kalaw@dlsu.edu.ph

Abstract: Readers experience various emotions while reading, which may affect their overall enjoyment and comprehension of the material. The current work presents a study on brainwaves or EEG signals and their association to emotions while a person is reading literary fiction. EEG data from 32 participants, aged 18 years old and above, were collected with the use of an EEG headset. We describe our methodology for data acquisition and processing, feature extraction and dataset building, as well as the classification experiments done.

Keywords: EEG, affect recognition, machine learning

1. Introduction and Challenges in Building the Reader Affect Model

People experience a variety of emotions while being engaged in certain activities. As shown in the studies of Azcarraga & Suarez (2012) and Yazdani et al. (2012), emotions evoked while being engaged in an activity could be detected via a person's brainwaves or electroencephalogram (EEG) data. The act of reading literary fiction is a profoundly emotional experience. Miall & Kuiken (1994) and Cupchik et al. (1998) are empirical works in the culture, media, and arts that have established the relation between reading and emotional response. The current work presents an EEG-based detection and recognition of emotions while a person is reading literary fiction.

Collecting the data, obtaining the ground truth, and defining the appropriate emotion model are some of the challenges in building any affective model (Picard, 2003). For this study, we used an Emotiv Insight EEG headset (https://www.emotiv.com/insight/), which can capture data from the *AF3*, *AF4*, *T7*, *T8*, and *Pz* channels, with the convenience of a dry sensor. In obtaining the ground truth, a self-reporting scheme was integrated with the developed data collector tool. For the emotion model, two models were considered. The *Hourglass of Emotion* (HoE) model by Cambria et al. (2012) describes what is the person feeling. They described their model as one that is able to represent affective states both through its labels and its 4 independent but co-occurring affective dimension–namely, *aptitude*, *attention*, *pleasantness*, and *sensitivity*. In this way, their model can potentially describe a full range of emotional experiences. Whereas, the *Emotions of Literary Response* (ELR) model by Miall & Kuiken (2002), describes if the emotions were caused by overall enjoyment in reading the text (*evaluative feelings*), by the events or characters in the fictional world (*narrative feelings*), or by the formal components of the text (*aesthetic feelings*).

2. Methodology

2.1 Data Acquisition and Processing

EEG signals from 32 participants of various demographics were collected while they were reading *The Veldt* by Ray Bradbury. Prior to the experiment proper, the participants were asked to close their eyes and relax for 2 minutes. This recording serves as the baseline. Following the experimental set-up of Miall & Kuiken (1994) for the presentation of the stimuli, the story was manually divided into 72 segments using phrase and sentence divisions while still retaining meaning and coherence by itself. The story segments were presented one by one via the data collector tool adapted from Azcarraga & Suarez (2012). After reading the segment, the participant would annotate what they felt and what caused it. The read-annotate process is repeated until the last segment is reached. Note that the EEG recording while the participants are reading is called the event-related potentials (ERP).

Data preprocessing includes synchronizing the ERP recording with the emotion annotations, dividing the data into the corresponding story segments, and then further subdividing each segment into 2-second windows with 1-second overlap. The total number of these windows represents the number of instances for a particular participant.

2.2 Feature Extraction and Dataset Building

EEG frequency bands were extracted via a series of band pass filters. For each band, the signals were transformed to the frequency domain using a fast Fourier transform algorithm, and then the minimum, maximum, and mean values for each feature type were computed. The feature types are *magnitude*, which is the absolute value of the signal; *power spectral density* (PSD), which is the square of the signal in the frequency domain; and spectral power of asymmetric electrode pairs via *differential asymmetry* (DASM), or power subtraction, and *rational asymmetry* (RASM), or power division. This makes a total of 252 extracted features for each instance.

Each instance is labeled according to the self-reported emotion annotations the participants made. With regard to the HoE, the participants were asked to rate each of the 4 dimensions from -3 to +3. If the value is negative, the assigned label is *low*. If the value is positive, then the assigned label is *high*. With regard to the ELR, whichever the participant chose is the assigned label. It is possible for the instance to have multiple assigned labels for ELR.

The current work is concerned with the brainwaves of participants during reading time. These brainwaves (ERP) are isolated by employing baseline correction, which is simply subtracting the *i*th feature value of the baseline from all the ERP instances (Woodman, 2010). After performing baseline correction and building the datasets according to the profile groups, the datasets are standardized by computing for the z-score values. Extreme z-score values were clipped to at least -3 and at most +3.

3. Preliminary Results

The experiments conducted are binary classifications of the HoE and ELR models on different datasets (Female, Male, Sex-merged) and classification methods (Decision Tree (DT), Support Vector Machine (SVM), Multilayer Perceptron (MLP)). Across all classification experiments, the classifiers were trained with *leave-one-participant-out cross-validation*. Refer to Table 1 and Table 2 for the listing of averaged f-measure values of the classification experiments.

Table 1: F-measure values for the HoE class labels.

DT (F)	DT (M)	DT	SVM (Base)	MLP (Base)	SVM (PCA)	MLP (PCA)
44.28	46.12	49.53	46.52	52.04	47.51	48.86

The first experiment was to set the baseline performance using Decision Trees and to see whether there is an improvement in performance among the specific datasets and the general dataset. It is observed that on an average basis, there is no significant improvement in the performance between the general profile dataset and the specific datasets (refer to columns 1 to 3).

The next experiment was to attempt to improve the classification performance with SVM and MLP classifiers. As discussed in the previous section, there is no significant improvement in the performance between the general profile dataset and the specific datasets; therefore, the general dataset is the one used in this experiment. It is observed that MLP yields a slightly better performance than DT (refer to columns 3 to 5).

The last experiment was to see whether reducing the number of features via PCA could yield a result that is higher than or at least at par with the base feature set. It is observed that the performance of the classifiers with PCA feature sets yield subpar results to that of its counterpart with the base set of 252 EEG features. The average difference in the f-measure value of the Base classifiers and PCA classifiers for both SVM and MLP is ±2 (refer to columns 4 to 7). Note that the processing of the SVM and MLP classifiers takes much of the computer's resources. Thus, if it is acceptable to have a ±2 margin of error, then using the PCA feature set would suffice as compensation for faster processing time.

Table 2: F-measure values for the ELR class labels.

DT (F)	DT (M)	DT	SVM (Base)	MLP (Base)	SVM (PCA)	MLP (PCA)
52.38	45.22	45.32	44.25	52.01	43.15	49.60

4. Future Work

We describe a methodology for building a reader affect model based on EEG signals collected from 32 participants. Inferences from our preliminary results are consistent with the emotion study of Kret and De Gelder (2012); however, further research and analysis is recommended.

Further work will consider strategies for improving the classification performance results, exploring the use of deep learning, and visualizing and showing the trajectory to discover patterns in reading behavior and preferences. Other experiments can explore *intra-subject* classification, wherein the same methodology may be repeated except that the stories that a single participant reads subscribe to one of the 6 core emotional arcs (Reagan, Mitchell, Kiley, Danforth, & Dodds, 2016). The current work makes use of the first impressions of the participants towards the story. Following what Tompkins (1980) said that reading is an experience that is never the same from one reading to the next, this could be tested by having the participant repeat the data acquisition process for a number of times. In this way, the fourth domain in the ELR model, *self-modifying feelings*, which involves the restructuring of the reader's understanding of the textual narrative, could potentially be mapped. The trajectory in the change of emotions for the same stimuli could be observed.

For intelligent tutors and embodied conversational agents, the resulting models can be used as basis for the conversation topic with the reader, to address factors affecting one's engagement with the reading task and comprehension of the reading materials.

Acknowledgements

We would like to acknowledge the support and funding provided by the DOST-ERDT program.

References

Azcarraga, J., & Suarez, M. T. (2012). Predicting academic emotions based on brainwaves, mouse behaviour and personality profile. In P. Anthony, M. Ishizuka, & D. Lukose (Eds.), *PRICAI 2012: Trends in Artificial Intelligence* (pp. 728–733). Springer Berlin Heidelberg.

Cupchik, G. C., Oatley, K., & Vorderer, P. (1998). Emotional effects of reading excerpts from short stories by James Joyce. *Poetics*, *25*(6), 363–377.

Kret, M. E., & De Gelder, B. (2012). A review on sex differences in processing emotional signals. *Neuropsychologia*, *50*(7), 1211–1221.

Miall, D. S., & Kuiken, D. (1994). Foregrounding, defamiliarization, and affect: Response to literary stories. *Poetics*, *22*(5), 389–407.

Miall, D. S., & Kuiken, D. (2002). A feeling for fiction: Becoming what we behold. *Poetics*, *30*(4), 221–241.

Picard, R. W. (2003). Affective computing: challenges. *International Journal of Human-Computer Studies*, *59*(1), 55–64.

Reagan, A. J., Mitchell, L., Kiley, D., Danforth, C. M., & Dodds, P. S. (2016). The emotional arcs of stories are dominated by six basic shapes. *EPJ Data Science*, *5*(1), 31.

Tompkins, J. P. (1980). The reader in history: The changing shape of literary response. *Reader-Response Criticism: From Formalism to Post-Structuralism*, *201*.

Woodman, G. F. (2010). A brief introduction to the use of event-related potentials in studies of perception and attention. *Attention, Perception, & Psychophysics*, *72*(8), 2031–2046.

Yazdani, A., Lee, J.-S., Vesin, J.-M., & Ebrahimi, T. (2012). Affect Recognition Based on Physiological Changes During the Watching of Music Videos. *ACM Transactions on Interacive Intelligent Systems*, *2*(1), 7:1–7:26.