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

Analyzing Novice Programmers' EEG Signals using Unsupervised Algorithms

Vanlalhruaii SWANSI[a*], Tita HERRADURA[a,b] & Merlin Teodosia SUAREZ[a]

[a]*Center for Empathic Human-Computer Interactions,*
College of Computer Studies, De La Salle University, Philippines
[b]*College of Science and Computer Studies,*
De La Salle University – Dasmarińas, Philippines
*m_swansi@yahoo.com, trherradura@dlsud.edu.ph, merlin.suarez@delasalle.ph

Abstract: Ten (10) first year college programming students participated in the study and reported their emotions during the learning session. Emotiv EPOC headset was used to gather EEG brainwave signals. Digital signal processing filtering technique was used to filter the data. The reported academic emotions were *engaged, confused, frustration* and *boredom*. A square SOM map with 10 rows by 10 columns was built to visualize the EEG data set, a total of 100 nodes. The weights of the final SOM nodes were clustered using k-medoids and k-means algorithms, both derived two main clusters; one cluster aptly named *"State of hope and enthusiasm"* because it is primarily composed of clusters of *confused* emotion nodes surrounded by a topographical arrangement of *engaged* emotion nodes; the other cluster named *"State of frustration and boredom"* because it is primarily composed of *frustrated* and *boredom* emotion nodes. These observations of the topographical arrangements of the SOM nodes and its subsequent clustering of the SOM nodes by k-medoids and k-means, seem to be in accordance with previous findings by (Kort, Reilly & Picard, 2001; D'Mello & Graesser, 2011) ultimately making SOM to be a viable and good alternative representation/visualization tool for D'Mello's theory of academic affect transition model. We also observed that k-medoids required much lesser number of *k* to derive similar clusters of SOM nodes as k-means, moreover, execution time for k-medoids is the same as k-means, making k-medoids a very attractive option for clustering algorithm of choice for clustering of SOM nodes.

Keywords: Affective Computing, Academic emotions, EEG data, Self-organizing Maps, Clustering algorithms.

1. Introduction

Students working on a complex task like solving problems, writing a computer program may experience varied emotions. Dr. Rosalind Picard stated that emotions play a vital role in learning since thinking and feeling are mutually present in normal human cognition (Picard, 1995). Thus, cognitive and affective states of a learner are crucial; similarly with affective transitions in order provide the necessary interventions to support learning (D'Mello & Graesser, 2012). Emotions are detected during learning by various physiological sensors (Frasson and Chalfoun, 2010). Electroencephalography (EEG) is a technique for reading scalp electrical activity (Teplan, 2002). Academic emotions are detected via EEG signals and are not easily faked (Mampusti, Ng, Quinto, Teng, Suarez and Trogo, 2011). The EEG signals are alpha, beta, delta and theta. Beta waves are high range frequency, an alert state, implying an increase in cognitive efforts (Boutros, Galderisi & Pogarell, 2011). This study deals with beta EEG brainwave signals.

(Craig et al., 2004) defined academic emotions as *engagement* being positive emotion and *boredom, frustration* and *confusion* as negative emotions and should be handled in an Intelligent Tutoring System (ITS) for necessary intervention to support learning.

2. Related Works

Transitions occur between academic emotions (D'Mello & Graesser, 2011), when progress is blocked, a student experiences *confusion*, when resolved, it transitions to *engagement* (see Figure 1). When *confusion* is not resolved, frustration occurs resulting in interplay between *confusion* and *frustration*. When *frustration* persists, *boredom* sets in, resulting in interplay between *frustration* and *boredom* (Bosch & D'Mello, 2013; Bosch & D'Mello, 2015).

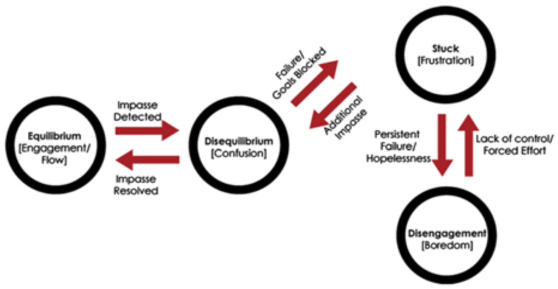

Figure 1. Theoretical model of affect transitions.

3. Methodology

The participants were ten (10) first year college students from DLSU–Dasmariñas, Philippines. Raw EEG signals were collected from students engaged in computer programming using Emotiv EPOC head set. Data gathering techniques were based on the work by (Azcarraga, Marcos & Suarez, 2014).

Beta waves were extracted using a digital bandpass filter (1000th- order) with passband of 14-30 Hz. The bandpass filter used hamming windowing method. The filtered signals are then subjected to Fourier analysis and statistical features were extracted from the dataset.

4. Results and Discussions

The EEG data set with 48 features and 4,000 instances were analyzed using unsupervised learning algorithms like Self Organizing Maps (SOM), k-medoids and k-means clustering algorithms.

(Kangas, Kohonen and Laaksonen, 1990; Ritter and Kohonen, 1989) used SOM to represent abstract data relationship via topographic maps. A square map with a total of 100 nodes was built. Initial neighborhood was the entire SOM map and highest initial *learning rate* was 0.9 and 0.1 the lowest. To ensure fair selection process a random single sample *x* was selected from the dataset and *exponential decay* function was used. SOM was implemented two times, implementation #1 seems to have stabilized at 35,000th iteration and implementation #2 seems to have stabilized at 30,000th iteration.

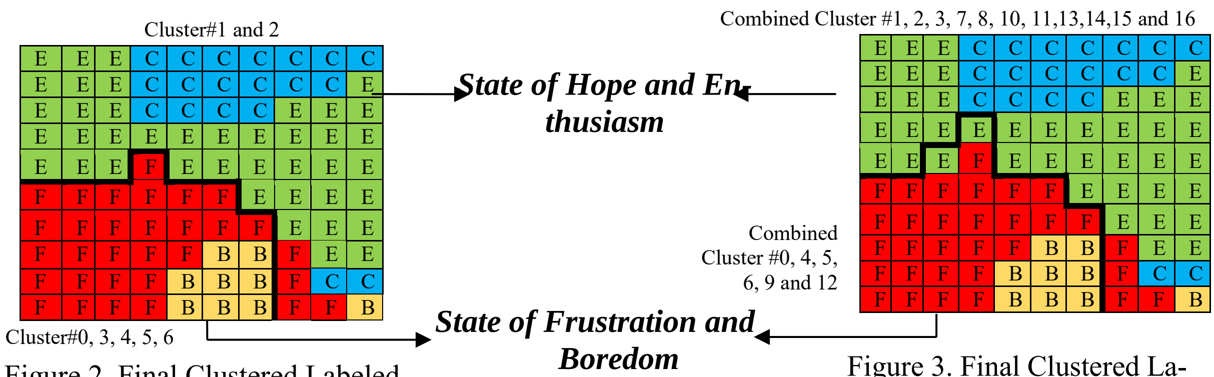

Figure 2. Final Clustered Labeled SOM map using K-Medoids when k=7

Figure 3. Final Clustered Labeled SOM map using K-Means when k=16

To identify similar nodes of the SOM, K-Medoids and K-Means clustering algorithms were applied. K-medoids takes the most centrally located object in the cluster (i.e. median) and K-means takes the mean value (i.e. average). Figure 2 shows a SOM with K-medoids when k=7 and Figure 3 shows a SOM with K-means when k=16, the clusters derived by both algorithms are very similar to each other.

The right hand side of the map in Figure 2 and Figure 3 is dominated by *confused* and *engaged* emotions and appear to conform to the *state of hope and enthusiasm* as mentioned in (Kort, Reilly and Picard, 2001; Rodrigo, Baker and Nabos, 2010). The left hand side clusters of the map is dominated by *frustrated* and *bored* emotion nodes and labeled as *state of frustration and boredom* and appear to be consistent with (Graesser and D'Mello, 2011)'s cognitive disequilibrium model which states that *confusion* has to be resolved and if it goes unresolved, *confusion* will lead to *frustration* and *boredom*.

K-medoids required much lesser number of *k* (*k*= 7) to derive similar clusters of SOM nodes as K-means (*k*=16) and execution time for k-medoids is the same as k-means, making K-medoids a very attractive option for clustering algorithm of choice for clustering of SOM nodes.

5. Conclusions and Recommendation

SOM allowed us to determine relationships based on which nodes are adjacent to each other while k-medoids and k-means determined the relationship based on which nodes are included in the cluster, making the analysis more meaningful and interesting. We may infer that SOM is a viable and good alternative representation/visualization tool for D'Mello's theory of academic affect transition model.

Future works include increasing the number of participants and implementing the above analysis on adult learners' EEG dataset.

References

Azcarraga, J., Marcos, N., Suarez, M.T., (2014), Modelling EEG Signals for the Prediction of Academic Emotions, First Workshop on Utilizing EEG Input in Intelligent Tutoring Systems (ITSWEEG), *12th International Conference on Intelligent Tutoring Systems*, Honolulu, Hawaii.

Bosch, N., & D'Mello, S. (2013, June). Sequential patterns of affective states of novice programmers. In *The First Workshop on AI-supported Education for Computer Science (AIEDCS 2013)* (pp. 1-10).

Bosch, N., & D'Mello, S. (2015). The Affective Experience of Novice Computer Programmers. *International Journal of Artificial Intelligence in Education*, 1-26.

Boutros, N., Galderisi, S., Pogarell, O. (2011). Standard Encelophagraphy in Clinical Psychiatry, *A Practical Handbook,* Wiley.

Craig, S. D., Graesser, A. C., Sullins, J., and Gholson, B. (2004). Affect and learning: An Exploratory Look into the Role of Affect in Learning with Autotutor. *Journal of Educational Media*.

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction*, *22*(2), 145-157.

Frasson, C., Chalfoun, P. (2010). Managing Learner's Affective States in Intelligent Tutoring Systems. *Advances in Intelligent Tutoring Systems*. Springer Berlin Heidelberg. pp 339-358.

Graesser, A., & D'Mello, S. K. (2011). Theoretical perspectives on affect and deep learning. In *New perspectives on affect and learning technologies* (pp. 11-21). Springer New York.

Kangas, J. A., Kohonen, T. K., &Laaksonen, J. T. (1990). Variants of self-organizing maps. Neural Networks, IEEE Transactions on, 1(1), 93-99.

Kort, B., Reilly, R., Picard, R. (2001). An affective model of interplay between emotions and learning. In: Proceedings of IEEE International Conference on Advanced Learning Technologies, pp. 6–8

Mampusti, E., Ng, J., Quinto, J., Teng, G., Suarez M., Trogo R. (2011). Measuring Academic Affective States of Students via Brainwave Signals. *Third International Conference on Knowledge and Systems Engineering (KSE)*.

Picard, R. (1995). Affective Computing. Technical Report 321, MIT Media Laboratory, MIT Media Laboratory: Perceptual Computing; 20 Ames St., Cambridge, MA 02139.

Ritter, H., & Kohonen, T. (1989). Self-organizing semantic maps. Biological cybernetics, 61(4), 241-254.

Teplan, M. (2002). Fundamentals of EEG Measurement. *Measurement Science Review*, Volume 2, Section 2, Institute of Measurement Science, Slovak Academy of Sciences, Slovakia.