Recognizing Reader's Affect Using EEG Data

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by

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Chapter 1

Research Description

This chapter introduces the research undertaken in the field of Affective Computing. It is divided into four sections which discusses the research problem, the research objectives, the scope and limitations, as well as the significance of the study.

1.1 Overview of the Current State of Technology

Although emotion theorists still do not have a clear definition as to what emotions are (Kleinginna Jr. & Kleinginna, 1981), many studies suggest that emotions or affect play vital roles in rational and intelligent behavior such as cognition and decision making (Bechara, Damasio, & Damasio, 2000; Schwarz, 2000). Emotions interplay with rational thinking in ways that are imperceptible but important for intelligent functioning. Humans already observe emotional intelligence (EI), which is a subset of social intelligence that involves the ability to monitor one's own and others' feelings and emotions, to discriminate among them and to use this information to guide one's thinking and actions (Salovey & Mayer, 1990). Ciarrochi et al. (2000) presents a critical evaluation of the importance of EI versus the intelligence quotient (IQ). They conclude that while a number of people claim that EI is more important than IQ, there is little scientific evidence to support said claim. However using the Multi-factor Emotional Intelligence Scale (MEIS), they were able to justify some of the claims of EI like being an important determinant of success in relationships and careers.

With regards to affective computing —which relates to, arises from, or influences emotions— it is simply imbuing a computer the capability to have emotional intelligence. Imagine a computer that is aware of your psychological well-being, e.g. mental or emotional state. Theoretically, its responses would adjust accordingly depending on your current mental state. Thus, affective interactions with computers can easily and immediately give direct feedback as opposed to human interactions (Picard & Picard, 1997). But before computers can give feedback, it has to detect a person's psychological state first. This is where emotion recognition comes in.

Humans usually perceive emotions by facial or vocal expressions. However, there are other physiological cues such as knowing that a person is nervous because their hand is clammy when you held it (relating to skin conductance); or determining that a person is excited when you feel their pulse (relating to heart rate). Hence, people naturally read many physiological signals of emotions (Picard, 2000). Translating this to computers, emotion recognition involves physiological pattern recognition. This proves to be a challenge because, again, there is no clear definition for what emotions are, and there is still the issue whether there are distinct physiological patterns that are associated with each emotion (Cacioppo & Tassinary, 1990). Regardless of the difficulty, there have already been various studies in emotion detection and recognition for various domains and motivations. Such detection is possible through analysis of facial and/or vocal expressions (Zeng et al., 2006; Zeng, Pantic, Roisman, & Huang, 2007), a combination of physiological data (e.g., heart rate, skin conductance, muscle tension) (Picard, Vyzas, & Healey, 2001; Harris et al., 2014), or even something as unusual as mouse-click behavior (Azcarraga & Suarez, 2013; Sun, Paredes, & Canny, 2014).

Electroencephalography (EEG) is the recording of the brain's electrical activity and represents a way to look at the brain functions in real time (Rossetti & Laureys, 2015). The brain's electrical activity or brainwaves is another example of physiological data. EEG is a noninvasive procedure and can be recorded digitally with commercial portable devices such as Emotiv EPOC/EPOC+[1], Muse[2], or iBrain[3]. In the field of medicine, EEG evaluation has played critical roles in accurate patient diagnosis, seizure detection, evaluation of patients with consciousness disorders, and even sleeping disorders. Whereas in the field of affective computing, EEG serves as a standalone or an additional modality for affect detection and recognition. Azcarraga and Suarez (2013) uses EEG coupled with mouse-click behavior to predict academic emotions (confidence, excitement, frustration, and interest) of students while solving varying difficulty levels of math equations. Leslie et al. (2014, 2015) utilizes EEG and motion capture to study the engage-

[1]Emotiv, https://emotiv.com/
[2]InteraXon, http://www.choosemuse.com/
[3]Neurovigil, http://www.neurovigil.com/

ment of people while listening to music. Sano and Picard (2014) uses EEG and a combination of other physiological data measured by a multi-modal wearable wrist sensor to classify whether a patient is asleep or awake. Lastly, Yazdani et al. (2012) utilized EEG and peripheral physiological data to recognize affect while participants are watching music videos.

Reading literary texts or fiction is not simply an activity but rather an experience that is never the same from one reading to the next (Tompkins, 1980). It is a pleasurable activity when the reader's imagination is engaged in an active and creative way (Iser, 1972). Reading non-fiction differs from reading fiction. Usually, when one reads non-fiction such as memoirs or news articles, the goal is to be informed. Whereas when one reads fiction such as novels, short stories, or poems, the goal is to be entertained and moved (experience a variety of emotions) (Mar, Oatley, Djikic, & Mullin, 2011). The act of reading literary fiction is part of a broader aspect of human growth and development based on understanding one's own experiences and the social world (Freire & Slover, 1983). Mar et al. (2009) and Kidd and Castano (2013) proves that reading improves a person's empathy and theory of mind —the ability to impute mental states (i.e. beliefs, intents, desires, pretending, knowledge) to the self and others and to understand that others have their own beliefs, desires, intentions, and perspectives that are different from one's own (Doherty, 2008). Vezzali et al. (2015) proves this when they showed how reading Harry Potter improves attitudes (reduces prejudices) towards out-group individuals, i.e. immigrants, homosexuals, refugees.

Reader-response criticism —a school of literary theory that focuses on the *reader*, the *reading process*, and *response*, rather than the literary text itself — is said to have started with I.A. Richard's discussion of emotional response (Tompkins, 1980). There have been empirical studies that have attempted to correlate reading and the emotional response. Oatley (1995) states that emotions (typically happiness, sadness, anger, fear, disgust) are triggered by an event and are often with physiological accompaniments such as a change in heart rate, facial expressions. His taxonomy of emotions on literary response is based on literary criticism and cognitive psychological theory. Emotions arising from reading the literary text, also called narrative emotions, are the following: emotions of sympathy, relived emotions, and emotions of identification. Mar et al. (2011) modified this taxonomy by adding two more: emotions of empathy and remembered emotions.

There have been empirical works that have established the relation between reading and emotions in the culture, media, and arts research area.Cupchik et al. (1998) showed how different literary texts elicits different emotional responses (emotions of identification vs. remembered emotions). Miall and Kuiken (1994) tested how stylistic variations (foregrounding) in the literary text affects the response of people in terms of reading time, strikingness, and affect. However, there is no current work that has studied brainwave patterns and their association to affect while a person is reading literary fiction.

1.2 Research Objectives

1.2.1 General Objective

To build an affect model that associates the EEG signals collected from readers (while they are reading stories) to specific emotions.

1.2.2 Specific Objectives

1. To review the approaches, methodologies, and experiments of existing affect detection or recognition studies that uses EEG data;
2. To identify the different emotions the can be elicited from the readers by the stories;
3. To build a corpus of EEG signals;
4. To determine which elements of a story affects the reader's emotional state;
5. To implement supervised and unsupervised machine learning algorithms for classifying the emotion based on the EEG signals;
6. To define evaluation metrics for assessing the performance of the model;

1.3 Scope and Limitations of the Research

The research will focus on EEG data as its modality for emotion detection and recognition. A review of existing affect detection or recognition studies that uses EEG data is needed in order to determine what are the approaches and techniques in tackling this area of research. It includes, but not limited to, the review of how the data is collected and prepared, how did their studies conduct their tests and experiments, what are the machine learning algorithms and the features that they used to train their models. Aside from emotion detection of recognition studies, a review of researches establishing the association of affect and EEG is also needed.

In order to associate the brainwave patterns to specific emotions, the research must identify these specific emotions first. This will entail a review of different emotion models and determine which of them is appropriate for reader affect.

For the computer to be able to associate patterns of brainwaves to specific affect, a data corpus of EEG signals must be built. The participants will be people of ages between 18 to 25 of diverse demographics. Participants will read pre-selected short stories recommended by the resource person while an EEG sensor is attached to them. Short stories is the chosen literary fiction in order for each participant to read the text in one sitting. Similar to the experiments of Miall and Kuiken (1994), these short stories have been segmented, which is checked and approved by the resource person as well. The set-up of Miall and Kuiken (1994) and Yazdani et al. (2012) will be used as basis for the data collection methodology.

The study will attempt to determine which element of the story triggered the reader to evoke that emotion. The story elements are limited to character traits and behavior, the reader's empathy to the character, the story plot or casual chain of story events, and lexical choices and sentence structure.

Weka or Rapidminer is being considered to perform the classification. This study will identify unsupervised or supervised classification techniques best suited for the data.

The usual metrics for machine learning —precision, recall, and f-measure — will be used to evaluate the performance of the affect model.

1.4 Significance of the Research

Affective computing is a relatively new field that does not use new technologies. It is a combination of various existing technologies and computer science concepts like wearable devices, digital signal processing, computer vision, pattern recognition, machine learning, and human-computer interaction. This study can contribute the feasibility of these technologies and concepts on an unexplored application domain. This study provides a basis of the brainwave activity of people to their emotions while they are reading, compared to their self-reported emotions. The methodology on data collection, data preparation, pre-processing, and classification will also be useful to future studies relating to EEG.

The results of this study can provide more understanding to emotions, which can be further utilized in affect-related systems such as intelligent tutoring systems (ITS) or embodied conversational agents (ECA). Aside from the field of computer science, the contributions of this work may be informative to affective science and psychology as well. Testing may be further extended to other age groups to provide a comparison of each age group's affective states on a certain literary text. In-depth comparison studies of affective states per demographic profile can also be done.

References

Azcarraga, J., & Suarez, M. T. (2013). Recognizing Student Emotions using Brainwaves and Mouse Behavior Data. *International Journal of Distance Education Technologies (IJDET)*, *11*(2), 1–15.

Bechara, A., Damasio, H., & Damasio, A. R. (2000, March). Emotion, Decision Making and the Orbitofrontal Cortex. *Cerebral Cortex*, *10*(3), 295–307. Retrieved 2016-02-26TZ, from http://cercor.oxfordjournals.org/content/10/3/295 doi: 10.1093/cercor/10.3.295

Cacioppo, J. T., & Tassinary, L. G. (1990). Inferring psychological significance from physiological signals. *American Psychologist*, *45*(1), 16. Retrieved 2016-02-26TZ, from http://psycnet.apa.org/journals/amp/45/1/16/

Ciarrochi, J. V., Chan, A. Y. C., & Caputi, P. (2000, March). A critical evaluation of the emotional intelligence construct. *Personality and Individual Differences*, *28*(3), 539–561. Retrieved 2016-02-26TZ, from http://www.sciencedirect.com/science/article/pii/S0191886999001191 doi: 10.1016/S0191-8869(99)00119-1

Cupchik, G. C., Oatley, K., & Vorderer, P. (1998). Emotional effects of reading excerpts from short stories by James Joyce. *Poetics*, *25*(6), 363–377. Retrieved 2016-01-25TZ, from http://www.sciencedirect.com/science/article/pii/S0304422X98900079

Doherty, M. J. (2008). *Theory of mind: How children understand others' thoughts and feelings*. Psychology Press. Retrieved 2016-02-27TZ, from https://www.google.com/books?hl=en&lr=&id=NB15AgAAQBAJ&oi=fnd&pg=PP1&dq=theory+of+mind+Doherty&ots=j3PrFsrq-e&sig=U0H-UZB-paqN4aCd6gw66N2MTuI

Freire, P., & Slover, L. (1983). The importance of the act of reading. *Journal of education*, 5–11. Retrieved 2016-02-27TZ, from http://www.jstor.org/stable/42772842

Harris, A., Hoch, A., Kral, R., Teposte, M., Villa, A., Chavez-Echeagaray, M. E., ... Atkinson, R. K. (2014). Including Affect-driven Adaptation to the Pac-Man Video Game. In *Proceedings of the 2014 ACM International Symposium on Wearable Computers: Adjunct Program* (pp. 1–4). New York, NY, USA: ACM. Retrieved 2016-02-15TZ, from http://doi.acm.org/10.1145/2641248.2641360 doi: 10.1145/2641248.2641360

Iser, W. (1972). The reading process: A phenomenological approach. *New literary history*, *3*(2), 279–299. Retrieved 2016-02-27TZ, from http://www.jstor.org/stable/468316

Kidd, D. C., & Castano, E. (2013). Reading literary fiction improves theory of mind. *Science*, *342*(6156), 377–380. Retrieved 2016-02-27TZ, from http://science.sciencemag.org/content/342/6156/377.short

Kleinginna Jr., P. R., & Kleinginna, A. M. (1981, December). A categorized list of emotion definitions, with suggestions for a consensual definition. *Motivation and Emotion*, *5*(4), 345–379. Retrieved 2016-02-26TZ, from http://link.springer.com/article/10.1007/BF00992553 doi: 10.1007/BF00992553

Leslie, G., Ojeda, A., & Makeig, S. (2014). Measuring musical engagement using expressive movement and EEG brain dynamics. *Psychomusicology: Music, Mind, and Brain*, *24*(1), 75. Retrieved 2016-02-15TZ, from http://psycnet.apa.org/journals/pmu/24/1/75/

Leslie, G., Picard, R., & Lui, S. (2015). An EEG and Motion Capture Based Expressive Music Interface for Affective Neurofeedback. *1st International Workshop on Brain-Computer Music Interfacing*. Retrieved 2016-02-15TZ, from http://affect.media.mit.edu/pdfs/15.leslie-picard-lui.pdf

Mar, R. A., Oatley, K., Djikic, M., & Mullin, J. (2011). Emotion and narrative fiction: Interactive influences before, during, and after reading. *Cognition & emotion*, *25*(5), 818–833. Retrieved 2016-02-28TZ, from http://www.tandfonline.com/doi/abs/10.1080/02699931.2010.515151

Mar, R. A., Oatley, K., & Peterson, J. B. (2009). Exploring the link between reading fiction and empathy: Ruling out individual differences and examining outcomes. *Communications*, *34*(4), 407–428. Retrieved 2016-02-27TZ, from http://www.degruyter.com/view/j/comm.2009.34.issue-4/comm.2009.025/comm.2009.025.xml

Miall, D. S., & Kuiken, D. (1994, August). Foregrounding, defamiliarization, and affect: Response to literary stories. *Poetics*, *22*(5), 389–407. Retrieved 2016-01-28TZ, from http://www.sciencedirect.com/science/article/pii/0304422X94000115 doi: 10.1016/0304-422X(94)00011-5

Oatley, K. (1995, January). A taxonomy of the emotions of literary response and a theory of identification in fictional narrative. *Poetics*, *23*(12), 53–74. Retrieved 2016-01-28TZ, from http://www.sciencedirect.com/science/article/pii/0304422X94P4296S doi: 10.1016/0304-422X(94)P4296-S

Picard, R. W. (2000). Toward computers that recognize and respond to user emotion. *IBM systems journal*, *39*(3.4), 705–719.

Picard, R. W., & Picard, R. (1997). Affective computing.

Picard, R. W., Vyzas, E., & Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, *23*(10), 1175–1191.

Rossetti, A. O., & Laureys, S. (2015). *Clinical Neurophysiology in Disorders of Consciousness: Brain Function Monitoring in the ICU and Beyond*. Springer.

Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. *Imagination, cognition and personality*, *9*(3), 185–211.

Sano, A., & Picard, R. W. (2014). Comparison of sleep-wake classification using electroencephalogram and wrist-worn multi-modal sensor data. In *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE* (pp. 930–933). IEEE. Retrieved 2016-02-15TZ, from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6943744

Schwarz, N. (2000, July). Emotion, cognition, and decision making. *Cognition and Emotion*, *14*(4), 433–440. Retrieved 2016-02-26TZ, from http://dx.doi.org/10.1080/026999300402745 doi: 10.1080/026999300402745

Sun, D., Paredes, P., & Canny, J. (2014). MouStress: Detecting Stress from Mouse Motion. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 61–70). New York, NY, USA: ACM. Retrieved 2016-02-15TZ, from http://doi.acm.org/10.1145/2556288.2557243 doi: 10.1145/2556288.2557243

Tompkins, J. P. (1980). The reader in history: The changing shape of literary response. *Reader-response criticism: From formalism to post-structuralism*, *201*, 32. Retrieved 2016-01-25TZ, from https://www.google.com/books?hl=en&lr=&id=t472Hekz8JoC&oi=fnd&pg=PA201&dq=kinds+of+emotions+readers+feel&ots=LMczFtaDbi&sig=aWBg6-7QiVzCRBLYTWt0ENbNBEM

Vezzali, L., Stathi, S., Giovannini, D., Capozza, D., & Trifiletti, E. (2015). The greatest magic of Harry Potter: Reducing prejudice. *Journal of Applied Social Psychology*, *45*(2), 105–121. Retrieved 2016-02-27TZ, from http://onlinelibrary.wiley.com/doi/10.1111/jasp.12279/full

Yazdani, A., Lee, J.-S., Vesin, J.-M., & Ebrahimi, T. (2012, March). Affect Recognition Based on Physiological Changes During the Watching of Music Videos. *ACM Trans. Interact. Intell. Syst.*, *2*(1), 7:1–7:26. Retrieved 2016-01-30TZ, from http://doi.acm.org/10.1145/2133366.2133373 doi: 10.1145/2133366.2133373

Zeng, Z., Hu, Y., Fu, Y., Huang, T. S., Roisman, G. I., & Wen, Z. (2006). Audio-visual Emotion Recognition in Adult Attachment Interview. In *Proceedings of the 8th International Conference on Multimodal Interfaces* (pp. 139–145). New York, NY, USA: ACM. Retrieved 2016-02-15TZ, from http://doi.acm.org/10.1145/1180995.1181028 doi: 10.1145/1180995.1181028

Zeng, Z., Pantic, M., Roisman, G. I., & Huang, T. S. (2007). A Survey of

Affect Recognition Methods: Audio, Visual and Spontaneous Expressions. In *Proceedings of the 9th International Conference on Multimodal Interfaces* (pp. 126–133). New York, NY, USA: ACM. Retrieved 2016-02-15TZ, from http://doi.acm.org/10.1145/1322192.1322216 doi: 10.1145/1322192.1322216