Recognizing Reader's Affect Using EEG Data

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Abstract

Emotions or affect is known to play vital roles in rational and intelligent behavior such as cognition and decision making. Detecting or recognizing affect can be done by analyzing physiological data or a combination of various physiological data. One such example of a physiological data is the brain's electrical activity which is measured using an Electroencephalogram (EEG). EEG-based affect recognition has been done while a person is solving math problems, listening to music, watching movies, or watching music videos. This research proposes an EEG-based affect recognition model on an unexplored application domain, which is while a person is reading short stories.

Keywords: affective computing, affect recognition, EEG, digital signal processing, machine learning

Contents

1 Research Description **1**

1.1 Overview of the Current State of Technology 1

1.2 Research Objectives 3

1.2.1 General Objective 3

1.2.2 Specific Objectives 4

1.3 Scope and Limitations of the Research 4

1.4 Significance of the Research 5

1.5 Research Methodology 7

1.5.1 Concept Formulation and Literature Review 7

1.5.2 Development of Data Collector Tool 7

1.5.3 Data Collection and Corpus Building 7

1.5.4 Training and Evaluation 8

1.5.5 Documentation 8

1.5.6 Calendar of Activities 9

2 Review of Related Literature **10**

2.1 Emotions and Computing 10

2.2 Emotions and Brainwaves 12

2.3 Emotions and Reading Fiction 19

3 Theoretical Framework **20**

3.1 Electroencephalography 20

3.2 Emotiv Insight EEG Headset 21

3.3 Emotions 22

3.3.1 Importance of Emotions 22

3.3.2 Emotion Models 23

3.4 Reading Fiction 26

3.4.1 Reader-Response Criticism 26

3.4.2 Emotions of Literary Response 26

3.4.3 Age-Related Changes in Emotion Understanding and Reading Comprehension 28

4 Design and Implementation **29**

4.1 Research Framework 29

4.2 Selection of Short Stories 30

4.3 Data Collector Tool 31

4.3.1 Connector Module 33

4.3.2 Parser Module 37

4.3.3 Logger Module 39

4.4 Data Acquisition 39

4.5 EEG Processing 40

4.5.1 Preprocessing 40

4.5.2 Feature Extraction 41

5 Findings **44**

5.1 Experiment 1: Initial Data Collection and Preprocessing 44

5.2 Initial Findings 45

5.2.1 Reading Experience and Emotional Response 45

5.2.2 Software Usage 46

A Research Ethics Forms and Checklists **47**

B Informed Consent Form **61**

C Sample Segments of Selected Short Stories **65**

D Resource Persons **68**

References **69**

List of Figures

2.1 Experimental set-up of Yazdani et al. (2012) 14

2.2 Comparison of features before and after LDS. 15

3.1 Emotiv Insight device and control panel. 22

3.2 Dimensional emotion model by Russell (1980). 24

3.3 The Hourglass of Emotions model by Cambria et al. (2012). . . . 25

3.4 Taxonomy of Emotions of Literary Response. 27

4.1 Research framework for building the reader affect model. 29

4.2 Architecture of the data collector tool. 31

4.3 Screenshot of the data collector tool. 32

4.4 Data acquisition flowchart. 39

4.5 Pre-processing for EEG data during reading session 40

4.6 MATLAB `fdatool` session for delta δ band pass filter 42

4.7 Summary of features extracted from the data 43

List of Tables

1.1 Timetable of activities. 9

2.1 Five factors on obtaining *good* affect data. 12

2.2 Summary of MLP accuracy results of Azcarraga and Suarez (2012). 13

2.3 Summary of accuracy results of Yazdani et al. (2012). 14

2.4 Summary of accuracy results of Nie et al. (2011). 16

2.5 Summary of MLP accuracy results of Lin et al. (2010). 17

2.6 Summary of SVM accuracy results of Lin et al. (2010). 17

2.7 Summary of EEG-based affect recognition studies. 18

3.1 Different EEG frequency bands. 21

Listings

4.1 Code snippet for initializing the `EmotivConnector`. 33
4.2 Code snippet for initializing the `CameraConnector`. 33
4.3 Code snippet for `engine_UserAdded_Event` method. 34
4.4 Code snippet for Emotiv data capture threading. 35
4.5 Code snippet for capturing data from the Emotiv device. 36
4.6 Code snippet for `videoSource_NewFrame` method. 36
4.7 Code snippet for video recording. 36
4.8 Code snippet for stopping EEG recording. 37
4.9 Code snippet for stopping video recording. 38
4.10 XML representation of segmented *Man From the South* by Roald Dahl 38
4.11 eegfilt() definition 41
5.1 Logic error in code for logging timestamp. 45
5.2 Resolution to timestamp logging logic error. 45

Chapter 1

Research Description

This chapter introduces the research undertaken in the field of Affective Computing. It is divided into four sections which discuss 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) present 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. Note that the same stimulus creates different emotions in different individuals, and the same individual may express different emotions in response to the same stimulus, at different times.

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 a person's psychological well-being, that is his mental or emotional state. Theoretically, its responses would adjust accordingly depending on the person's current mental state. Thus, affective interactions with computers can easily and immediately give direct feedback as opposed to human interactions (Picard, 1997). However, 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 held (relating to skin conductance) or determining that a person is excited their pulse is felt (relating to heart rate). Hence, people naturally read many physiological signals of emotions (Picard, 2000). Translating this to computers, emotion recognition involves pattern recognition of physiological data. 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), or even something as unusual as mouse-click behavior (Azcarraga & Suarez, 2012).

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 that 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 while doing an activity, such as the study by Azcarraga and Suarez (2012) where they used EEG coupled with mouse-click behavior to predict academic emotions (confidence, excitement, frustration, and interest) of students while solving varying difficulty levels of math problems.

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

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 academic texts 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). 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). Emotions arising from reading the literary text are called *narrative emotions* (Mar et al., 2011).

There have been studies establishing the association of brainwave patterns and emotions while being engaged in an activity. Yazdani et al. (2012) made use of EEG and various physiological data to classify the valance, arousal, and preference of the participants on music videos. Nie et al. (2011) attempted to find the relationship of EEG and human emotions while watching movies. Lastly, Lin et al. (2010) applied machine learning algorithms to categorize EEG dynamics according to emotional states while listening to music. There have also been empirical works that have established the relation between reading and emotions or emotional response in areas of culture, media, and arts. Cupchik et al. (1998) showed how different literary texts elicit different emotional responses (emotions of identification vs. remembered emotions). Miall and Kuiken (1994) tested how stylistic variations 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 maps 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 use EEG data;
2. To identify different emotions that can be elicited from the readers as they read the stories;
3. To determine which elements of a story affect the reader's emotional state;
4. To build a corpus of EEG signals;
5. To implement machine learning algorithms for classifying the emotion based on the EEG signals; and
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 use EEG data is needed to determine what the approaches and techniques are in tackling this area of research. It includes the review of how the data are collected and prepared, how tests and experiments are conducted, what machine learning algorithms and features are 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.

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. The basis for *appropriateness* is dependent on the goal of the research and its participants. The academic emotion model is an example of a model that may not be aligned to the goal of this research. Ekman's model of six basic emotions (happiness, sadness, fear, anger, disgust, and surprise) may not be enough for the participants to fully articulate their emotional state.

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.

For the computer to be able to associate patterns of brainwaves to specific affect, a data corpus of EEG signals must be built. This will be collected from participants of ages between 18 and 25 of diverse demographics. (The rationale behind the 18 to 25 age group is that the short stories have appeared in must-read lists for *high school* and *college students*. Having said that, a younger age group may have difficulty in understanding the material itself, thus, may lead to negative emotions such as confusion and frustration. Furthermore, based on Hannon and Daneman (2009) and Phillips et al. (2002), younger and older adults more or less have similar reading comprehension abilities as well as understanding and decoding emotions from written passages (further explanation at Section 3.4.3. The maximum age of 25 is only tentative and may change if there is an older participant who wishes to take part in the experiment.) Data collection will follow the methodology of the studies mentioned in Section 2.2 while the presentation of the stimulus is similar to the experiments in the studies in Section 2.3. The chosen literary fiction are short stories because it can be read in a single sitting. The selected short stories are *The Veldt* by Ray Bradbury, *Man from the South* by Roald Dahl, and *The Fisherman and the Jinni* from *One Thousand and One Nights*. Since this proposed study involves the participation of human subjects, informed consent forms will be given to them following the ethical research guidelines of the university (refer to Appendix A and B).

Weka (Hall et al., 2009) are Rapidminer (Hofmann & Klinkenberg, 2013) are examples of some of the tools being considered to perform the machine learning tasks. Both are open source tools for data science tasks.

The usual metrics for supervised machine learning tasks, which are precision, recall, accuracy, and f-measure, will be used to evaluate the performance of the affect model. Unsupervised machine learning metrics will still be determined.

1.4 Significance of the Research

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

The results of this study can provide more understanding of emotions, which can be further utilized in affect-related systems such as intelligent tutoring systems (ITS) (Anderson, Boyle, & Reiser, 1985) or embodied conversational agents (ECA) (Cassell, 2000). These kinds of systems replicate face-to-face human interactions with, for example, a digital avatar. Since these systems serves as stand-ins for humans, it should at least, on a certain level, feel like having a natural interaction with a human, a teacher/tutor in the case of an ITS. For example, we have an ITS/ECA that helps a child practice reading. In reality, effective teachers gauge certain cues from its students and respond accordingly. If the system detects distress or frustration from the child based on his or her brainwaves, it can react appropriately. If the example system is more advanced, then it may determine where the distress or frustration is coming from, e.g. if the child's cause of frustration is the difficulty of the words, then the ITS can replace those words with easier ones.

Aside from the field of computer science, the contributions of this work may be informative to affective science and psychology as well. Various iterations of experiments can be done depending on research objectives such as in-depth comparative studies (per demographic profile, e.g. per age group, per gender) of affective states while reading. Emotion detection can also be an indicator for behavior prediction, most especially when monitoring certain emotional states that could lead to potentially harmful or dangerous behaviors.

From a business perspective standpoint, the contributions of this work may also be of use to product and market analysis. Given a narrative, product description, commercial script, or something of the same nature, the findings of this research will give insights to the public's or audience's response to the narrative. By knowing their target audience's likes or dislikes, companies can efficiently create more effective products or services. On the other perspective, i.e. the target audience of the business companies, knowing the emotions or the response of other buyers can give them more information on the product. This is why some people check the rating and reviews of a certain item or service before actually buying. However, not everyone rates and reviews items or services after they purchase it and if they do, it not as detailed as some would like it. So if there is some way to refine the rating and reviewing system to be automatic or semi-automatic and to present the detected emotions in an intuitive and objective manner, then the consumers could make informed decisions and know that the product or service is truly worth their money. Another example can be considering emotions as tags for content media retrieval such as looking for book recommendations that makes you feel happy.

1.5 Research Methodology

This section lists and discusses the phases and activities that are performed to accomplish the research project. The phases occur in a sequential manner unless otherwise stated. They are also revisited when new limitations are discovered.

1.5.1 Concept Formulation and Literature Review

This phase is concerned with the formulation of the thesis, particularly the identification of the research problem and its objectives, as well as defining its scope and limitations. A review of related literature on emotions, brainwaves, and reading fiction was done to understand how these concepts correlate with each other. The methodologies and approaches presented in some of these studies were considered to see if they are applicable to this research. The tools that are used are also learned in this phase in addition to canvassing and procuring the needed equipment. This phase is important because it builds the background knowledge needed before proceeding to the next phases.

1.5.2 Development of Data Collector Tool

In this phase, the tool to be used for data collection was developed. Prior to the development, the pre-selected short stories was split into segments while still retaining meaning and coherence per segment (see Appendix C for a sample of the short story segments used). The data collector tool was based on the system used by Azcarraga and Suarez (2012). The software tool output of this phase is relevant to the next phase.

1.5.3 Data Collection and Corpus Building

The data for training and evaluation of the affect model are collected in this phase. At least 30 participants will read the segmented short stories while an EEG sensor is attached to them. Their EEG recordings and self-assessments are gathered via the data collector tool described in the previous section. This phase may take up most of the duration of the research because each session per participant per story may last up to two (2) hours. Data preparation and pre-processing are also involved here. This phase may need to be repeated in case a larger corpus is required.

1.5.4 Training and Evaluation

This phase is involved with the application of the to-be-determined machine learning techniques as well as feature extraction and selection. Experiments include various combinations of machine learning techniques and feature sets applied to the data sets. The results of each model will be evaluated according to the metrics set in Section 1.3. This phase will also occur more than once as more data are added and new machine learning algorithms are discovered.

1.5.5 Documentation

The documentation phase is necessary all throughout the duration of the research. Taking down notes on the observations and findings during the other research activities and review of related literature, writing related technical documents, and the research paper itself fall under this phase.

1.5.6 Calendar of Activities

Table 1.1 shows the Gantt chart of the activities. Each asterisk represents approximately one week worth of activity.

Table 1.1: Timetable of activities.

Activities	Jan (2016)	Feb	Mar	Apr	May	Jun	Jul	Aug
Concept Formulation and Review of Related Literature	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆__				
Development of Data Collector Tool			__⋆⋆	⋆⋆__	⋆⋆__			
Data Collection and Corpus Building					__⋆⋆	⋆⋆⋆⋆	⋆⋆__	
Training and Evaluation							⋆⋆⋆⋆	⋆⋆⋆_
Documentation	__⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆__	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆_

Activities	Sep	Oct	Nov	Dec	Jan (2017)	Feb	Mar	Apr
Data Collection and Corpus Building			__⋆⋆	⋆___	⋆⋆⋆⋆	⋆⋆⋆⋆		
Training and Evaluation	_⋆⋆⋆	⋆⋆⋆⋆			⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆__	
Documentation	_⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆___	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆	⋆___

Chapter 2

Review of Related Literature

This chapter discusses the related studies to the research being undertaken. It presents how emotions are correlated to computing, brainwaves, and reading fiction.

2.1 Emotions and Computing

The field of Affective Computing was pioneered by Picard when she presented her ideas on the feasibility of affect-aware computers and possible implications and applications in 1995 (which eventually was published into a book in 1997). *Affective computing*, defined as computing that relates to, arises from, or influences emotions, is an aggregation of already existing technologies and computer science concepts such as wearable computing, digital signal processing, computer vision, pattern recognition, machine learning, and human-computer interaction. However, before Picard presented her ideas and theoretical applications on the field, she first justified as to why emotions should be imbued to computers (Picard, 1997).

Humans usually read and express emotions through face and voice. However, there are other physiological cues such as feeling clammy hands (relating to skin conductance) to mean that a person is nervous or having a fast heart rate to mean that a person is excited. Hence, people naturally read many physiological signals of emotions (Picard, 2000). Translating this to computers, emotion recognition involves pattern recognition of physiological cues. This proves to be a challenge because there is still the issue of whether there are distinct physiological patterns that are associated with each emotion (Cacioppo & Tassinary, 1990). A fast heart rate may imply that a person is either nervous or excited. So there must be other indicators that differentiate the two.

For an affect recognition system to be accurate, it needs to combine multiple kinds of physiological signals from the user as well as information about the user's context, situation, goals, and preferences (Picard, 1997). Picard (2000) attempted to classify a single person's physiological patterns of over a period of several weeks into eight distinct emotions. They used Clynes and Menuhin's set of emotions for their classification. The emotion set was chosen not because it is the best for HCI but rather because it has an already existing method for eliciting emotions (via *Sentograph*, also developed by Clynes and Menuhin). This set includes *no emotion (neutral)*, *anger*, *hate*, *grief*, *platonic love*, *romantic love*, *joy*, *reverence* with high/low arousal and positive/negative valence taken into consideration. Results show an 81% recognition accuracy on all eight classes of emotions.

Picard (2003) wrote a paper addressing most of the concerns and challenges in affective computing. One of the issues she points out was that her previous experiment (Picard, 2000) was forced to eight choices only. However, naturally we know that each emotion has its own varying degrees of intensity, thus, it is not only limited to eight. Picard gives an analogy to treat emotions like the weather. To quantify the weather, there are various sensors that measure temperature, pressure, humidity, etc. With emotions, it is building the sensors for the equivalents of temperature, pressure, etc. Like weather, the prediction may not be perfectly reliable, however, at least having a little foresight is useful.

Another issue Picard has addressed is with gathering *good* affect data. The first concern here are the sensors. Sensors are typically expensive, invasive, and/or obtrusive. There can be difficulty in gathering accurate physiological data due to technical factors such as the location where the sensors are applied, how much gel is used for the electrode. However, there are now advances in wearable technology that seamlessly integrates these sensors to what humans usually wear, i.e. the smart watch. Apart from the sensors, another challenge she present regarding affect data is the ground truth to compare the classifications to. An outsider cannot objectively say that the subject is feeling this certain emotion. Only the subject can know what emotional state he is in. If the outsider explicitly asks what the subject is feeling, that may also compromise the ground truth depending on how comfortable the subject is with expressing his feelings, how aware he is to his feelings, or if the subject becomes irritated with the constant asking of how he feels. Thus, Picard set the following factors on obtaining good affect data as show in Table 2.1. Underlined are the best conditions for gathering genuine affect data. The problem with it is that it is opportunistic and quite impossible to obtain as it breaches some privacy and ethical issues (Picard, 2000).

Table 2.1: Five factors on obtaining *good* affect data.

Subject-elicited vs. <u>event-elicited</u>	Does subject purposefully elicit emotion or is it elicited by a stimulus or situation outside the subject's efforts?
Lab setting vs. <u>real-world</u>	Is subject in a lab or in a special room that is not their usual environment?
Expression vs. <u>feeling</u>	Is the emphasis on external expression or on internal feeling?
Open-recording vs. <u>hidden-recording</u>	Does subject know that anything is being recorded?
Emotion-purpose vs. <u>other-purpose</u>	Does subject know that the experiment is about emotion?

2.2 Emotions and Brainwaves

Azcarraga and Suarez (2012) made use of EEG data coupled with mouse-click behavior to classify the academic emotions of the subjects. They have limited the academic emotions to *confidence*, *excitement*, *frustration*, and *interest* with the intensity taken into consideration. They used an Emotiv EPOC sensor, which has 14 channels, to record the EEG data and took note of the number of mouse clicks, each click's duration, and mouse movement. They first established the baseline EEG recording *resting state* by allowing the participant to relax for 3 minutes. The subjects were tasked to solve four algebra equations of varying levels of difficulty for a period of 15 minutes. A self-assessment window will pop up every 2 minutes and the participant will tag each academic emotion with intensity from 1 to 100 using their own developed observation module.

They have identified 17 features from the prepared data sets (14 EEG channels and 3 mouse behavior information) and used Multilayer Perceptrons (MLP) and Support Vector Machines (SVM), with 10-fold cross validation, as classification algorithms for their success in general approximation. Their metrics for assessing performance are precision, accuracy, and F-measure. Issues encountered in data preparation are with cleaning the data and balancing the data set. They had to manually synchronize the EEG recordings to the self-assessments. In addition, noise artifacts in the EEG which are not concerned with affective states were removed (i.e. blinking, hand movements), only 16 out of 25 data from the students were found useful given the conditions they set for balancing the data set. Six different datasets were prepared based on the percentage of feature outliers. A feature is considered an outlier if exceeds 1 standard deviation away from the mean of that particular feature of that particular subject. Their results show that as the number of outlier features increases, prediction accuracy also increases. The combination of brainwave and mouse behavior data yields better results than brainwave or mouse behavior alone. Note, however, that brainwave data performed better than mouse behavior data. On all cases of their experiments, MLP algorithm performed better than SVM. Table 2.2 shows a summary of their prediction accuracy results.

Table 2.2: Summary of MLP accuracy results of Azcarraga and Suarez (2012).

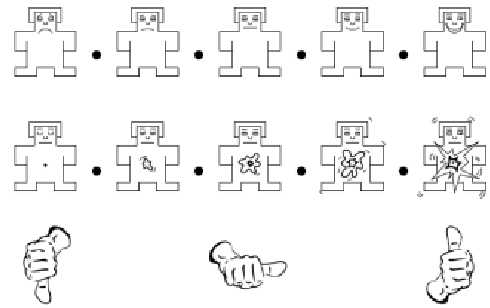
Dataset	**Brainwaves**	**Mouse**	**Brainwaves + Mouse**
0	54.66	32.26	61.04
10	63.74	38.9	69.8
25	75.27	45.11	78.58
33	74.92	45.46	80.69
50	83.65	43.85	88.56
60	88.33	48.79	92.27

Yazdani et al. (2012) combined EEG signals and various physiological signals in order to classify the emotional state of a person while they are watching music videos. Based on the valence-arousal scale proposed by Russell (1980), they classify the EEG and physiological signals into high/low arousal and positive/negative valence. They also added an additional like/dislike classification to see the preferences of their participants. They recorded the EEG and physiological signals using a BioSemi ActiveTwo system[4]. The EEG recording is composed of 32 channels and the accompanying physiological signals are the following: Galvanic Skin Response (GSR), respiration, skin temperature, blood volume pulse by plethysmograph, EMGs of of zygomaticus major and trapezius muscles (2 channels each), and a 4-channel electrooculogram (EOG). Figure 2.1a shows participant with the EEG and physiological sensors attached to him.

Their experiment started with having the participant relax for a period of two minutes, a fixation cross was displayed on the screen. This recording served as their baseline recording. 20 music video clips were presented at random in separate runs. Each run consists of a five-second baseline recording (display of the fixation cross), two-minute display of the music video, and the participant's self-assessment for his arousal, valence, and preference. Figure 2.1b shows the symbols that they used for the self-assessment, which was based on Morris's Self-Assessment Manikins (SAM). Preprocessing includes filtering, downsampling, and artifact removal to ensure artifact-free signals for all channels. They introduced a novel approach for feature extraction, which is using the relative wavelet energies (RWE) of each channel and the RWE of symmetrical channel pairs as extracted

[4] BioSemi, `http://biosemi.com/`

(a) A participant with the EEG and physiological sensors attached to him.



(b) Images used for self-assessment of (from top to bottom) arousal, valence, and preference.

Figure 2.1: Experimental set-up of Yazdani et al. (2012)

features. SVM classifier with radial basis function kernels and 20-fold cross validation was used in the classification. Table 2.3 shows the averaged accuracy of their results. Despite having the accuracy of the EEG data higher than the physiological data, their performance results are incomparable because they used different window lengths.

Table 2.3: Summary of accuracy results of Yazdani et al. (2012).

	Arousal	**Valence**	**Preference**
EEG Data	69.58%	73.66%	70.25%
Physiological Data	55.7%	54%	66.6%

An additional experiment that they explored was the feasibility of having a general-purpose affect recognition system. To test this, they trained a classifier on the physiological data of the participants and employed a leave-one-participant-out cross validation. They conclude that the accuracy varies among the participants, which indicates that classification is participant-dependent. Further investigation needs to be done to build a general classifier for all participants.

Nie et al. (2011) used EEG signals to classify *positive* and *negative* emotions while watching movie clips. Their rationale for only choosing two classes is because emotions come in mixed forms, hence, if the subject could not properly distinguish his emotions, he could at least identify whether it is a positive or a negative emotion. They used a 62-channel electrode cap to record the EEG with a 32-bit level at a sampling rate of 1000Hz.

Their experimental protocol is as follows. For each session, one movie clip is played. Five seconds to indicate the start of the session followed by a four-minute showing of the movie clip. After which, 45 seconds of self-assessment and then a 15-second rest before proceeding to the next session. They did not indicate whether they have a baseline recording of the participants before the experiment. For self-assessment, they used the SAM by Bradley and Lang (1994).

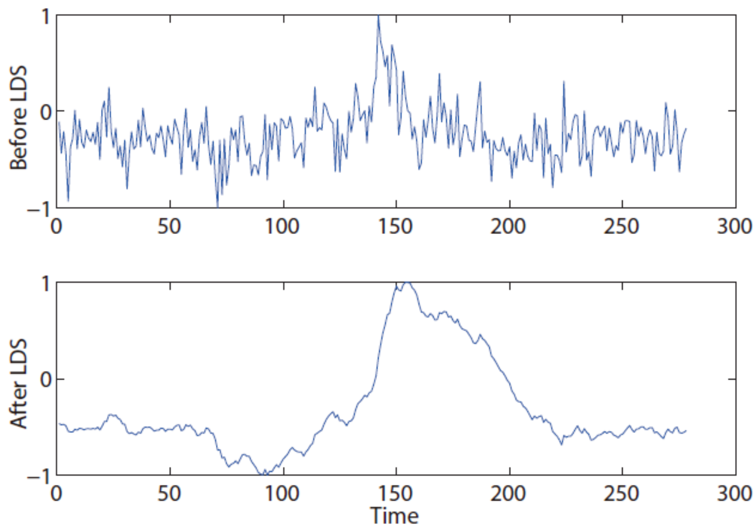


Figure 2.2: Comparison of features before and after LDS.

Data preparation and cleaning includes the removal of the artifacts not related to the emotional states and extracting the five frequency bands. To further remove noise, they smoothed the features by applying a linear dynamic system approach for each band. Figure 2.2 shows the difference of before and after using the LDS approach. For feature selection, they calculated the correlation coefficients between features and labels for each channel and band on the training set. They ranked them and obtained the top 50 and top 100 features. This is done in order to find subject-independent features. For classification, they used SVM with linear kernel to train the data for each band. This was done with a 7:3 ratio of training and testing data. Lastly, they employed another SVM for all of them. This was validated with a 10-fold cross validation. Table 2.4 shows the summary of prediction accuracy results of their classification.

Lin et al. (2010) applied machine learning algorithms in order to associate EEG patterns to self-reported emotional states while listening to music. The goal of their research was to identify emotion-specific EEG features as well as explore the efficiency of two classifiers, MLP and SVM. They used a 32-channel EEG module by Neuroscan, Inc. to record the EEG signals. Their emotion model is based on the four emotional states following the 2D arousal valence-arousal scale by Russell (1980): *joy* (positive valence, high arousal), *anger* (negative valence, high arousal), *sadness* (negative valence, low arousal), and *pleasure* (positive valence,

Table 2.4: Summary of accuracy results of Nie et al. (2011).

Subject	**Delta**	**Theta**	**Alpha**	**Beta**	**Gamma**	**ALL**
1	68.23	66.21	92.38	82.83	100	99.63
2	57.58	87.09	86.30	72.86	73.65	81.95
3	91.30	77.74	84.06	85.82	91.20	87.16
4	38.80	74.28	65.63	100	88.47	91.13
5	45.81	74.19	90.48	77.42	62.26	82.90
6	71.24	84.65	94.35	82.71	89.82	82.39
Average	62.16	77.36	85.53	83.61	84.23	87.53

low arousal). These emotional states were recorded with the use of FEELTRACE by Cowie et al. (2000).

From the recorded data, they have identified four feature sets. First is the individual spectral power from the 30 scalp electrodes (30 channels, namely Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, O1, Oz, and O2). The first feature set was named PSD30 for *power spectrum density for all 30 channels*. The next two feature sets involve the symmetric electrode pairs, namely Fp1-Fp2, F7-F8, F3-F4, FT7-FT8, FC3-FC4, T7-T8, P7-P8, C3-C4, TP7-TP8, CP3-CP4, P3-P4, and O1-O2. Asymmetry indexes were calculated in two ways. DASM12 (*differential asymmetry of 12 electrode pairs*) was computed by power subtraction (i.e. power of C3 - power of C4) whereas RASM12 (*rational asymmetry of 12 electrode pairs*) was computed by power division (i.e. power of C3 / power of C4). The last feature set is the PSD24 which is the *power spectrum density of 24 channels*. The PSD24 is a subset of PSD30 wherein the channels along the midline were not included (Fz, FCz, Cz, CPz, Pz, and Oz).

MLP and SVM classifiers were trained and evaluated with a 10-fold cross validation. Table 2.5 and Table 2.6 shows the results of their classification. DASM12 gave the best performance results among the frequency bands and general classifier of the frequency bands for SVM and MLP, with SVM having a marginally higher result. Since DASM12 gave the best results, they applied an F-score index with a leave-N-feature-out scheme to rank the features across all frequency bands. They obtained the top 30 subject-independent features and applied SVM, obtaining a result of approximately 74% accuracy.

Following Picard's five factors on obtaining good affect data, it is observed that Azcarraga and Suarez's, Yazdani et al.'s, Nie et al.'s, and Lin et al.'s experimental set-up is *event-elicited*, conducted in a *lab setting*, concerned with *feeling*, is *open-recorded*, and is *emotion-purpose*. Table 2.7 shows a summary of EEG-based affect

Table 2.5: Summary of MLP accuracy results of Lin et al. (2010).

Feature Type	EEG Frequency Band					
	Delta	Theta	Alpha	Beta	Gamma	All
DASM12	**63.93**	**63.67**	**64.07**	55.71	53.24	**81.52**
RASM12	48.54	50.69	55.40	48.21	44.82	65.33
PSD24	49.20	52.10	57.79	53.20	54.46	75.66
PSD30	52.12	55.61	61.89	**57.92**	**58.04**	79.54

Table 2.6: Summary of SVM accuracy results of Lin et al. (2010).

Feature Type	EEG Frequency Band					
	Delta	Theta	Alpha	Beta	Gamma	All
DASM12	**69.91**	**68.27**	**66.94**	**58.83**	57.35	**82.29**
RASM12	50.91	51.39	56.95	50.29	47.61	65.81
PSD24	51.02	53.27	54.61	55.42	56.80	69.54
PSD30	53.38	55.61	56.64	58.71	**59.54**	71.15

recognition studies while doing an activity.

Table 2.7: Summary of EEG-based affect recognition studies.

Reference	**EEG Recording**	**Emotion Model**	**Self-Assessment Scheme**	**Classification Algorithm**	**Features**	**Results**
Azcarraga, J., & Suarez, M. T. (2012). Predicting Academic Emotions Based on Brainwaves, Mouse Behaviour and Personality Profile.	14-channel Emotiv EPOC sensor	Confidence, interest, excitement, frustration	Own observation tool	MLP (10-fold cross validation)	Power spectrum density of 14 channels	54-88%
Yazdani, A., Lee, J.-S., Vesin, J.-M., & Ebrahimi, T. (2012). Affect Recognition Based on Physiological Changes During the Watching of Music Videos.	32-channel EEG electrodes recorded via Biosemi ActiveTwo system at 512Hz sampling rate	Arousal, valence, like/dislike	Morris's SAM for arousal and valence; thumbs up and down symbols for like/dislike	SVM with radial basis function kernel (20-fold cross validation)	Relative wavelet energies of each electrode together with RWE of symmetrical electrode pairs	69.58% (valence), 73.66% (arousal), 70.25% (like/dislike)
Nie, D., Wang, X.-W., Shi, L.-C., & Lu, B.-L. (2011). EEG-based emotion recognition during watching movies.	62-channel electrode cap recorded with 32-bit level at 1000Hz sampling rate	Positive, negative	Bradley's SAM	Linear SVM (7 [testing]:3 [training] ratio)	Top 100 and top 50 subject independent features obtained through the reduction of the original features by correlation coefficients	89.22% (Top 100), 84.94% (Top 50)
Lin, Y.-P., Wang, C.-H., Jung, T.-P., Wu, T.-L., Jeng, S.-K., Duann, J.-R., & Chen, J.-H. (2010). EEG-based emotion recognition in music listening.	32-channel module by Neuroscan, Inc. at 500Hz sampling rate	Joy, anger, sadness, pleasure	FEELTRACE	MLP, SVM with radial basis function kernel (10-fold cross validation)	Power spectrum density of 30 channels, differential asymmetry of 12 electrode pairs, rational asymmetry of 12 electrode pairs, power spectrum density of 24 channels	65-81% (MLP), 65-82% (SVM)

2.3 Emotions and Reading Fiction

There have been empirical works that have established the relation between reading and emotions or emotional response in areas of culture, media, and arts.

Miall and Kuiken (1994) observes how foregrounding, or stylistic variation in the text, influences the affect of the reader. *Foregrounding* refers to a range of stylistic variations that occur in literature at a phonetic level (alliteration, rhyme), grammatical level (inversion, ellipsis), or the semantic level (metaphor, irony). They have noted that readers are more likely to report the phrases that struck them or caught their eye when presented with the original text as opposed to one written in neutral terms. Hence, this means that foregrounding strikes interest. Their experiment consists of three literary stories, each short enough for an hour-long, single reading session. Each story contains a variety of foregrounded features and they were divided roughly into equal segments using phrase and sentence divisions while still retaining meaningful units as far as possible (approximately 77-86 segments per story). Their test subjects include both those with high and low literary competencies. For each participant, there were two readings. In the first reading, story segments are presented one at a time, with reference to the previous segment, and the current segment is highlighted. By the second reading, story segments are presented again one at a time, with reference to the two previous and succeeding segments. Then the participants are asked to rate the current segment based on strikingness (1 to 5 scale) and affect (no feeling to strong feeling). Their findings show that despite the test subjects having different interests and literary competencies, the affect of the reader to the story is independent. It may imply that only those with higher literary competencies draw more meaning on the text. Another finding they discovered is that the more foregrounded the segment, the more emotions it may elicit from the segment. In relation to the research project, this set-up seems like an appropriate methodology to adopt in the data gathering phase.

Cupchik et al. (1998) conducted a similar experiment but instead of focusing on what aspects of the texts elicited the emotional response, it is concerned with what type of emotional response the reader evoked. Their selected short stories were divided into four equal segments. Two of the stories have unifying emotional themes, while the other two were descriptively dense. The participants were instructed to either be a spectator and feel sympathy for the main character or to imagine oneself as the main character. After reading each segment, they were to rate the experience on 11-point scales measuring pleasure, intensity, and tension. Aside from rating, they were asked if they experienced *fresh emotions* (emotions of sympathy, identification, or empathy) or *emotional memories* (relived or remembered emotions).

Chapter 3

Theoretical Framework

This chapter discusses the theories and concepts needed to build the reader affect model.

3.1 Electroencephalography

Electroencephalography (EEG) is the recorded electrical activity generated by the brain (Rossetti & Laureys, 2015; *Brain Wave Signal (EEG) of NeuroSky, Inc.*, 2009). In the brain, there are millions of neurons which generates small electric voltage fields. The aggregation of these electrical activities is what the EEG electrodes are able to detect and record. EEG is an effective means of neuro-imaging because it is a noninvasive and safe procedure which can record in milliseconds. Event-related potentials (ERP) are the EEG signals time-locked to a stimulus which the participant reacts to. The baseline is the time period before the stimulus is presented. In the case of this research, reading the short stories serves as the ERP.

EEG is generally described in terms of its frequency bands. Each band has a certain frequency range and relates to various brain states as shown in Table 3.1.

Table 3.1: Different EEG frequency bands.

Brainwave Type	**Frequency Range**	**Mental States and Conditions**
Delta δ	0.1Hz to 3Hz	Deep, dreamless sleep, non-REM sleep, unconscious
Theta θ	4Hz to 7Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha α	8Hz to 12Hz	Relaxed, but not drowsy, tranquil, conscious
Low Beta β_1	12Hz to 15Hz	Formerly SMR, relaxed yet focused, integrated
Midrange Beta β_2	16Hz to 20Hz	Thinking, aware of self & surroundings
High Beta β_3	21Hz to 30Hz	Alertness, agitation
Gamma γ	30Hz to 100Hz	Motor functions, higher mental activity

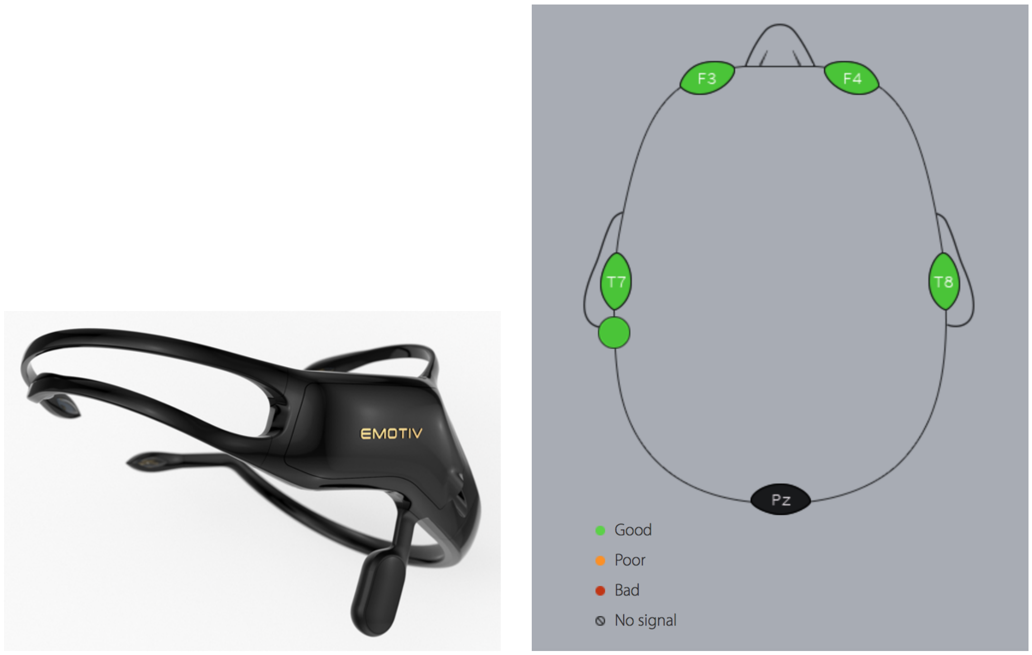
3.2 Emotiv Insight EEG Headset

The Emotiv Insight[5] is a 5-channel, wireless EEG headset that records brainwaves. It is a commercial product marketed worldwide and is designed for everyday use. It uses a polymer sensor that is safe to use and offers great electrical conductivity with the convenience of a dry sensor. These sensors read the brainwave signals and then transmits these signals to a computer via Bluetooth. Figure 3.1a shows what the device looks like whereas Figure 3.1b shows a screen capture of the device's control panel when it is connected to a computer.

This device has global recognition for its personal usage such as assessing athletic performance, cognitive training, or health and well-being. The technology is also backed and trusted by the scientific, academic, engineering and media communities and has been validated by many independent research papers[6].

[5]Emotiv Insight, `http://emotiv.com/insight/`

[6]Independent researches that used Emotiv, `http://emotiv.com/the-science/`



(a) Emotiv Insight (b) Emotiv Xavier Control Panel

Figure 3.1: Emotiv Insight device and control panel.

3.3 Emotions

3.3.1 Importance of Emotions

Kleinginna Jr. and Kleinginna (1981) compiled a categorized list of emotion definitions. This list is comprised of 92 definitions and 9 skeptical statements from various emotion theorists and sources of emotion literature. Despite the plethora of definitions, the relevance of emotions in a person's day-to-day activities has been proven by various studies. Examples of these studies are that of Bechara et al. (2000) and Schwarz (2000), which show the role of emotions in intelligent behavior.

In the field of neurology, Bechara et al. (2000) posit that the decision-making process is consciously or unconsciously influenced by marker signals arising from bioregulatory processes. These bioregulatory processes include those that are expressed in emotions. Decision-making is subserved in the orbitofrontal cortex of the brain as well as other cortical and subcortical areas. They have shown that lesions in the ventromedial (VM) prefontal cortex, a region of the brain which is involved in emotional response, seriously impairs the efficiency of decision making. The same goes for substance abusers and people with psychiatric disorders.

In social psychology, Schwarz (2000) points out the interplay of emotions, cognition, and decision making. He identifies scenarios and studies showing the role of emotions in various stages of decision-making. Before actually making a decision, a person's emotional state serves as a bias towards one of the options. Similarly, after a decision is made, there is an emotional reaction (e.g. regret, disappointment). Aside from the emotions elicited before and after making a decision, anticipated affect and memories of past affect also come into play. Anticipated affect simply means that a person is motivated to choose a certain option because he wants to avoid, for example, disappointment (anticipated affect). The same goes for memories of past affect, wherein instead of anticipating a certain emotion, the person already knows that a particular emotion is a likely outcome due to having already experienced it before.

A body of intelligence terminologies concerning affect was coined by Salovey and Mayer (1990). They define *emotional intelligence* (EI) as the 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. Ciarrochi et al. (2000) present 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.

3.3.2 Emotion Models

A challenge for affect recognition is determining the appropriate emotion model to be used. The reason for this problem goes back to the unclear definition of emotions. With reference to the numerous research done in emotion theory, it has resulted to two general kinds of emotion models: the categorical models and the dimensional models.

Categorical models are those that define a number of discrete basic emotions. Ekman (1972) is an example of this model. He defines six basic emotions: happiness, sadness, fear, anger, disgust, and surprise. In contrast, dimensional models describe the components of emotions and are often represented as a two- or three-dimensional space where the emotions are presented as points in the coordinate space of these dimensions. The arousal-valence scale by Russell (1980) is an example of this model, as shown in Figure 3.2. The dimension *valence* provides information about the degree of pleasantness of the content and ranges from pleasant (positive) to unpleasant (negative), while the dimension of *arousal* represents

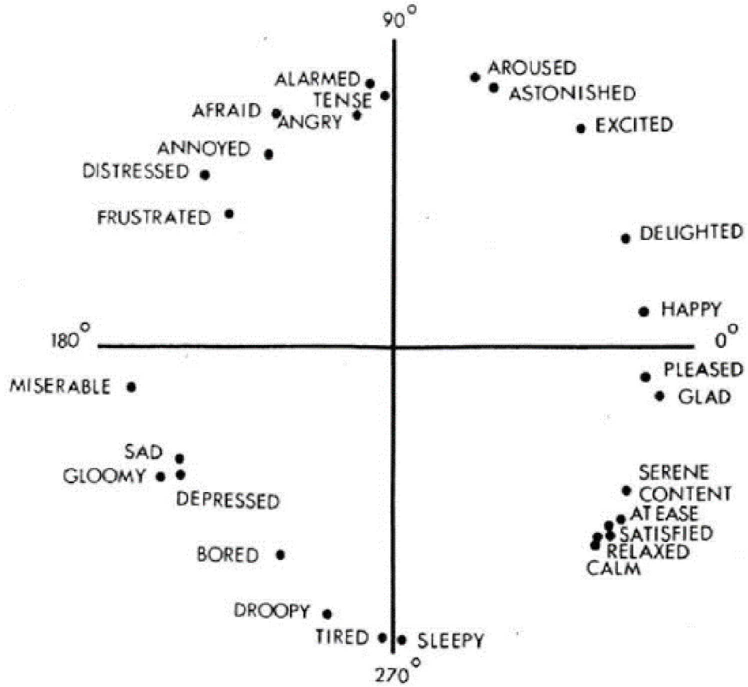


Figure 3.2: Dimensional emotion model by Russell (1980).

the inner activation and ranges from energized to calm.

Given the difference in these two kinds of emotion models, Cambria et al. (2012) proposed a novel biologically-inspired and psychologically-motivates emotion categorization model in which they dub as the *Hourglass of Emotion.* They describe the model as one that is able to represent affective states both through its labels (categorical) and its four independent but co-occurring affective dimensions (dimensional). In this way, they state that their model can potentially describe a full range of emotional experiences. Given this, this emotion model was chosen for this research.

The Hourglass of Emotions model, as shown in Figure 3.3, reinterprets Plutchik (2001) by organizing the primary emotions around four independent but related dimensions. These dimensions measure how much the user is amused by interaction modalities (*Pleasantness*), interested in interaction contents (*Attention*), comfortable with interaction dynamics (*Sensitivity*), and confident in interaction benefits (*Aptitude*). Each affective dimension is described by six *sentic levels* which is a measuring of the strength of an emotion.

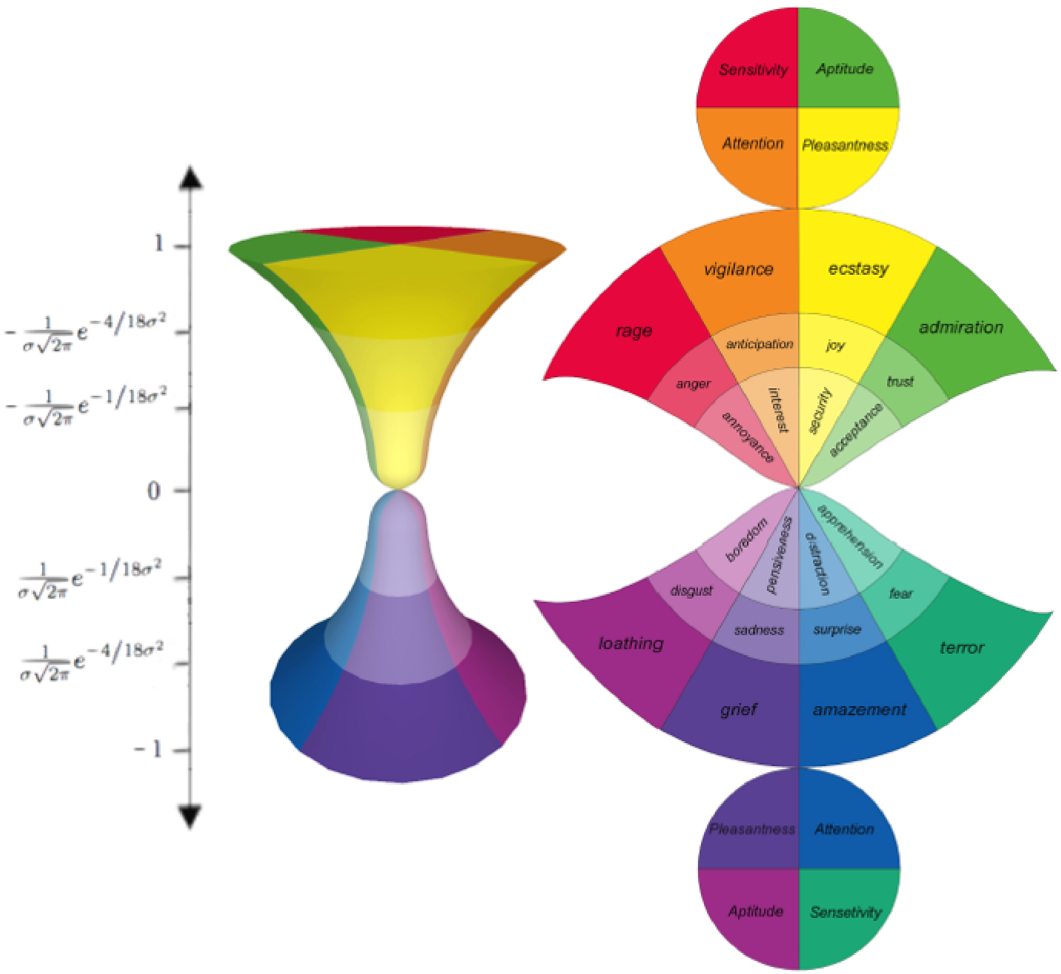


Figure 3.3: The Hourglass of Emotions model by Cambria et al. (2012).

3.4 Reading Fiction

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). It is an experience is never the same from one reading to the next (Tompkins, 1980). Mar et al. (2009) and Kidd and Castano (2013) proves that reading improves a person's empathy and *theory of mind*, defined as 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, e.g. immigrants, homosexuals, refugees.

3.4.1 Reader-Response Criticism

Reader-response criticism is a school of literary theory that focuses on the *reader*, the *reading process*, and *response*, rather than the literary text itself. It is said to have started with I.A. Richard's discussion of emotional response (Tompkins, 1980). Emotions are central to the experience of reading literary narrative fiction. A person's affect and mood influences and is being influenced before, during, and after the actual reading. Mar et al. (2011) cites current empirical studies on emotions and narrative fiction at each stage of reading. The research being done focuses on the emotions evoked during reading.

3.4.2 Emotions of Literary Response

Oatley (1995) presents a taxonomy of emotions in literary response. Emotions evoked when looking at a piece of fiction from a distance, evaluating its craft, style, and the like are called *aesthetic emotions*. The focus of this research are the *narrative emotions*, which are emotions concerning with entering the narrative world. Narrative emotions are further subdivided into three kinds. *Sympathy* is when the reader is a witness to the scene but unable to affect the action in any way. *Emotion memories* is when the text makes the reader remember a past feeling, thus, emotion memories are not only recalled but also relived. *Emotions of identification* is when the reader takes on the characteristics and goals of the character. This taxonomy is further extended by Mar et al. (2011). It included *emotions of empathy*, which is closely related to emotions of sympathy and identification.

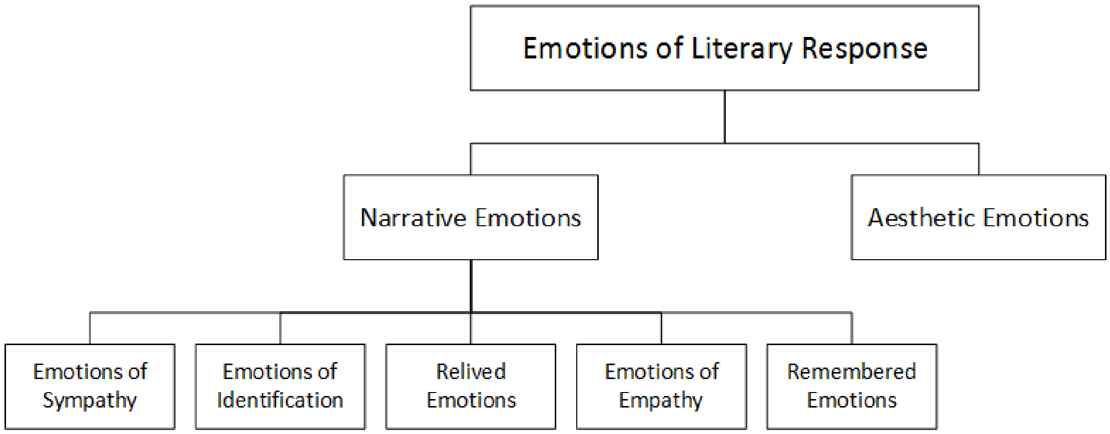


Figure 3.4: Taxonomy of Emotions of Literary Response.

Here, the reader does not identify with the character but rather empathizes with it. Emotion memories are split into relived emotions and remembered emotions. *Relived emotions* come from a recollection of past personal experiences whereas *remembered emotions* is a recalled emotion that does not fall under past personal experiences. This latest taxonomy is shown in Figure 3.4.

Miall and Kuiken (2002) describes another classification of emotions for literary response. Basic emotions, such as anger or fear, cannot fully encapsulate the feelings evoked during reading. Hence, they posit that these feelings can be roughly sorted into four domains. There is no specific distinction among these four because the reader may experience them simultaneously. However, they argue that each feeling domain can be differentiated on certain structures and processes. *Evaluative feelings* are those concerned with the overall enjoyment, pleasure, or satisfaction of reading the text. They can be emotions in response to the other domains. *Narrative feelings* are evoked by events or characters in the fictional world of the text. Emotions of sympathy or empathy are in this domain. *Aesthetic feelings* are prompted by the formal (generic, narrative, or stylistic) components of a text. These reflect the heightened interest of the reader when they encounter a passage so striking that it holds their attention. Lastly, *self-modifying feelings* restructure the reader's understanding of the textual narrative and, simultaneously, the readers sense of self. In relation to this research, it is only concerned with the first three. Notice that this classification coincides with the fourth specific objective of this research. Hence, this will be the chosen classification of emotions for literary response along with the notion that it also covers the other classification.

3.4.3 Age-Related Changes in Emotion Understanding and Reading Comprehension

Hannon and Daneman (2009) conducted an experiment to show the age-related changes in reading comprehension between young adults (people of ages 18-25) and older adults (people of ages 64-87) based on four components: text memory (tested memory for information explicitly presented in the paragraph), text inferencing (tested inferences about information that was implied in the paragraph), knowledge integration (required participants to access prior knowledge and integrate that knowledge with text information), and knowledge access (tested access to prior knowledge). Their results shows that those four components are susceptible to decline with aging. However, they also conclude that overall reading comprehension ability remained the same regardless of the age of their participants. With regards to understanding and decoding emotions from written passages, Phillips et al. (2002) reveals that there is no difference between young adults (people of ages 20-40) and older adults (people of ages 60-80). In summary, younger and older adults more or less have similar reading comprehension abilities as well as understanding and decoding emotions from written passages.

Chapter 4

Design and Implementation

This chapter presents the design and implementation on how to build the reader affect model. It covers the research framework and how some phases of the research methodology were realized.

4.1 Research Framework

The framework for the experiment of the research being undertaken is presented in Figure 4.1. It begins with the collection of the EEG data from a subject while he is reading the short story. After processing and preparing the data, different machine learning techniques are applied in order to build the reader affect model. A detailed discussion is presented in the subsequent sections.

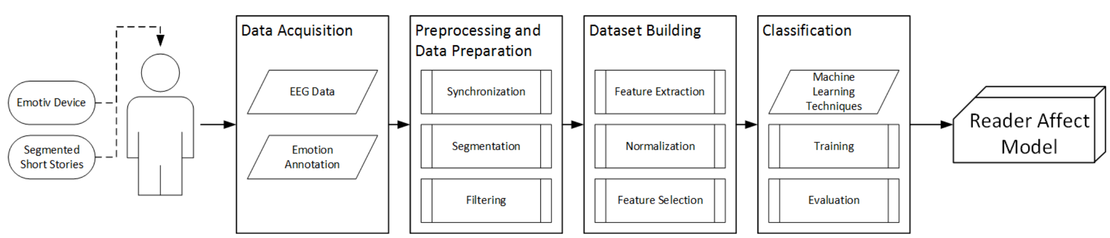


Figure 4.1: Research framework for building the reader affect model.

4.2 Selection of Short Stories

The short story is considered the most viable form of narrative for this research since it will entail a brief period of reading time (more or less than an hour). This delimitation is set in response to the perceived short attention span of teenage students. Nonetheless, the proposed selections are deemed some of the best in the world and have appeared in must-read lists for high school students. Another criterion is that these selections are deemed to contain prominent levels of emotional resonance (e.g. surprise, confusion, horror, pathos, shock, amusement) due to the clever use of narrative devices by the authors (e.g. suspense, atmosphere, mood, intrusion of the fantastic, characterization). These selections are recommended by the resource person from the creative writing department of the university. The proposed selections are:

- ***The Lovely House* by Shirley Jackson** tells of a young girl Margaret who spends one summer vacation with her friend in the latter's ancestral house. It is a ghostly tale concocted in the Gothic tradition. Shirley Jackson (American author, 1916-1965) is known for the *subversive impact* of her work, for her disquieting portrayal of history and society.

- ***The Veldt* by Ray Bradbury** is a story of a family who lives in an automated house with machines and gadgets that do all the work for them. This house has a nursery room that is able to create virtual realities in response to the telepathic wishes of the children. The finale of this science fiction masterpiece is quite disturbing. Ray Bradbury (American author, 1920-2012) is one of the foremost science fiction writers of the 20th century, known for his compelling visions of a dystopic world.

- ***Gangrene* by F. Sionil Jose** is a moving story about a brief reunion between a father and his son in an army hospital in Sierra Madre. The father is a brain surgeon of the Philippine Army, while the son is with the insurgents. The boy lies dying in the hospital room after he has been captured and tortured. Francisco Sionil Jose (Filipino author, 1924-present) is National Artist for Literature. His stories, vividly realistic and socially relevant, are canonical representations of Philippine traditions.

- ***Man from the South* by Roald Dahl** is set in a Jamaican hotel, where a chance encounter takes place between a South American man and a boy. It is a story about a strange bet. Roald Dahl (British author, 1916-1990) wrote such children's classics as *Charlie and the Chocolate Factory* and *James and the Giant Peach*. He is famous for his macabre short fiction, tinged with dark humor, irony, and surprise ending.

- ***The Fisherman and the Jinni*** **from** ***One Thousand and One Nights*** is a tale-within-a-tale, filled with magic and sorcery. It begins with an unfortunate meeting between a fisherman and a jinni, and ends with a marvelous tale of a prince and his enchanted kingdom. *One Thousand and One Nights* (ca. 850 AD) is deemed the first novel in the annals of world literature. Composed of several tales of wonder and framed within other narratives, this significant work, originally of Indian, Persian and Arabic origins, is a classic of all times. Its juicy tales are satires of human follies and foibles.

From these proposed selections, each story was read while being timed to get an idea of how long reading each story will take. *Gangrene* and *The Lovely House* took relatively longer to read (approximately 1 hour and 15 minutes versus approximately 40 minutes), thus, the remaining three are chosen for the experiments.

4.3 Data Collector Tool

Figure 4.2 presents the architectural design of the data collector tool. It consists of three main modules, which are the connector, parser, and logger, and is developed in C#. The connector module is responsible for integrating external devices, such as the Emotiv device, to the data collector tool. The parser converts the story file into a data structure for the tool. Finally, the logger handles the creation of the output files. Figure 4.3 shows a screen shot of the tool when in use.

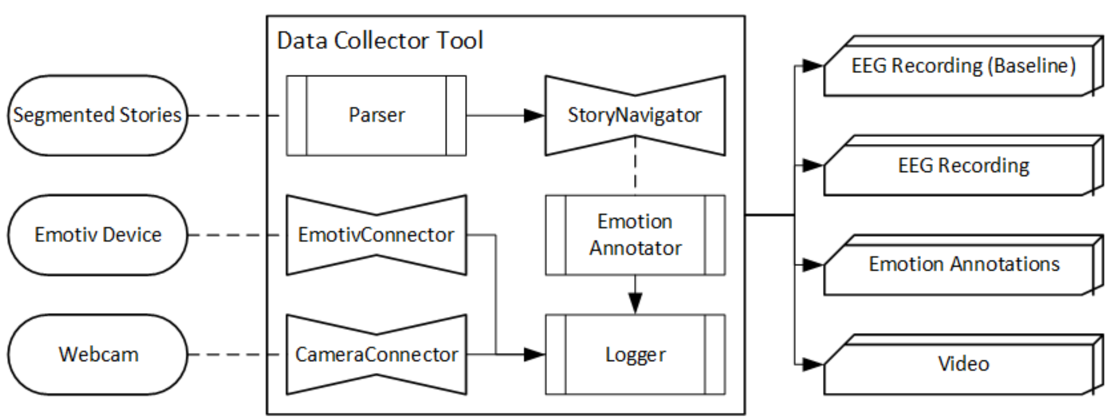
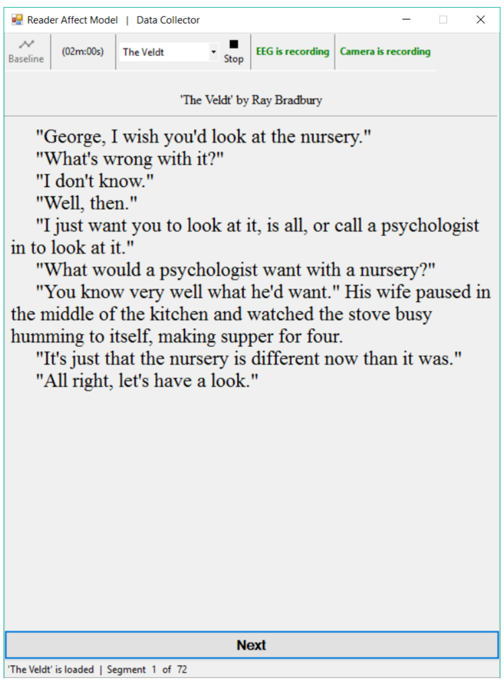
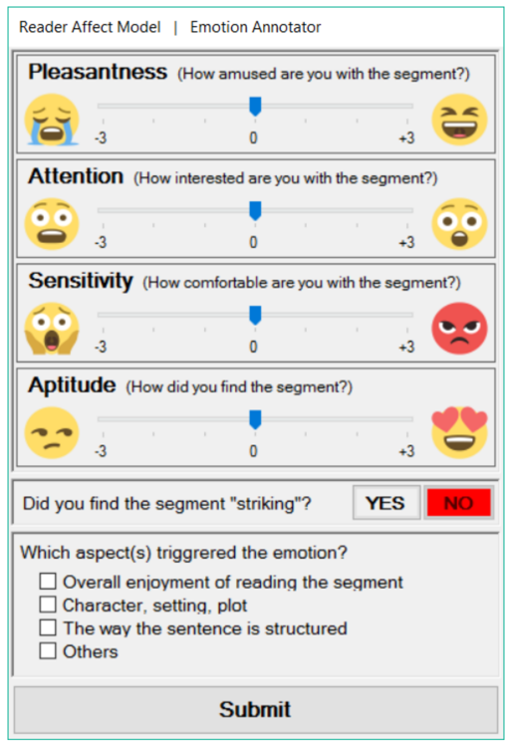


Figure 4.2: Architecture of the data collector tool.



(a) How the segments are presented



(b) Emotion annotation

Figure 4.3: Screenshot of the data collector tool.

4.3.1 Connector Module

This module has two classes `EmotivConnector` and `CameraConnector`, which handles the connection of the Emotiv Insight and the machine's native webcam, respectively. `EmotivConnector` uses the Emotiv SDK[7] whereas `CameraConnector` makes use of AForge.NET[8]. Both connectors essentially provide methods for initializing the connection to the devices, thread for data recording, and means of stopping the data capture.

Connector Initialization

```
EmoEngine engine;
int userID = -1;
  . . .
// Constructor
public EmotivConnector() {
  // Create an instance of the EmoEngine
  engine = EmoEngine.Instance;

  // Add user event handler
  engine.UserAdded += new EmoEngine.UserAddedEventHandler(engine_UserAdded_Event);
}
```

Listing 4.1: Code snippet for initializing the `EmotivConnector`.

```
VideoCaptureDevice videoSource;
  . . .
// Constructor
public CameraConnector() {
  // List all available video sources. (Video sources can be webcams as well as tv cards, etc)
  FilterInfoCollection videosources = new FilterInfoCollection(FilterCategory.VideoInputDevice);

  // Check if at least one video source is available
  if(videosources != null) {
    // Set the videoSource
    videoSource = new VideoCaptureDevice(videosources[0].MonikerString);

    // Create NewFrame event handler. Triggers every time a new frame/image is captured.
    videoSource.NewFrame += new AForge.Video.NewFrameEventHandler(videoSource_NewFrame);
  }
}
```

Listing 4.2: Code snippet for initializing the `CameraConnector`.

For both cases, it starts by referencing the accompanying .NET dll files. Access to the Emotiv device is through the `EmoEngine` object while access to the webcam is through the `VideoCaptureDevice` object. Listing 4.1 and 4.2 shows

[7] Emotiv SDK, `https://github.com/Emotiv`

[8] AForge.NET framework, `http://www.aforgenet.com/`

the code snippet for initialization of the `EmotivConnector` and `CameraConnector`, respectively.

Start Data Capture

After initializing the access objects, methods for handling connection events are added. When an Emotiv device connects to the tool, the `engine_UserAdded_Event` method is invoked, as shown in Listing 4.3. Note that this only prepares the tool for data capture, not record the EEG data yet. The method for capturing the EEG data is located in another thread. This is in order to allow simultaneous execution with the other methods, such as going to the next story segments, recording the emotions annotations, or recording the video. Listing 4.4 shows the code snippet on how the threading is done while Listing 4.5 shows the code for recording the EEG data.

```
private void engine_UserAdded_Event(object sender, EmoEngineEventArgs e) {
  // Record the user
  userID = (int)e.userId;

  // Enable data aquisition for this user.
  engine.DataAcquisitionEnable((uint)userID, true);

  // Ask for up to 1 second of buffered data
  engine.EE_DataSetBufferSizeInSec(1);
}
```

Listing 4.3: Code snippet for `engine_UserAdded_Event` method.

Likewise, the `videoSource_NewFrame` method is triggered whenever a new frame is captured for video recording, as shown in Listing 4.6. To begin video recording, simply call the `StartRecording` method. There is no need to explicitly create a thread for this part of the module. The code snippet can be seen in Listing 4.7.

Stop Data Capture

Let's say the main execution is handled by `Thread A`. When the data capture is prompted, `Thread B` is spawned to handle EEG recording. The main execution of going through the story segments and logging the data annotations still resides in `Thread A`. Hence, it will be `Thread A` that will send the signal to `Thread B` to stop recording the EEG through `volatile`[9] `bool _shouldStop`, as shown in Listing 4.8.

[9] `volatile` C# Reference, `https://msdn.microsoft.com/en-us/library/x13ttww7.aspx`

```
// Main
public partial class MainFrame : Form {
  private static EmotivConnector emoConnector;
  private Thread thdEmotivConnector;
    . . .
  emoConnector.Connect();
  StartEegComponent();
    . . .
  // Starts the EEG recording
  private void StartEegComponent() {
    // Create the thread object. This does not start the thread.
    thdEmotivConnector = new Thread(emoConnector.StartRecording);

    // Start the worker thread.
    thdEmotivConnector.Start();
  }
}

public class EmotivConnector {
  // Flag for telling the thread to begin terminating.
  private volatile bool _shouldStop;
    . . .
  // Connects the tool to the headset.
  public void Connect() {
    _shouldStop = false;
    userID = -1;

   // Connect to EmoEngine.
   engine.Connect();
  }

  // Prompts the tool to start capturing data from the device.
  public void StartRecording() {
    while(!_shouldStop) {
      Record();
      Thread.Sleep(delay);
    }
    engine.Disconnect();
  }
}
```

Listing 4.4: Code snippet for Emotiv data capture threading.

```
// Logs the values captured from the device to the output CSV file.
public void Record() {
  // Handle any waiting events
  engine.ProcessEvents();

  // If the user has not yet connected, do not proceed
  if((int)userID == -1)
    return;

  Dictionary<EdkDll.EE_DataChannel_t, double[]> data = engine.GetData((uint)userID);

  if(data == null)
    return;

  int _bufferSize = data[EdkDll.EE_DataChannel_t.ES_TIMESTAMP].Length;

  // Write the data to a file
  for(int i = 0; i < _bufferSize; i++)
    log.Log(Utilities.GetCsvTimestamp(), data[EdkDll.EE_DataChannel_t.AF3][i],
    ↪   data[EdkDll.EE_DataChannel_t.T7][i], data[EdkDll.EE_DataChannel_t.O1][i],
    ↪   data[EdkDll.EE_DataChannel_t.T8][i], data[EdkDll.EE_DataChannel_t.AF4][i]);
}
```

Listing 4.5: Code snippet for capturing data from the Emotiv device.

```
private void videoSource_NewFrame(object sender, AForge.Video.NewFrameEventArgs eventArgs) {
    . . .
  // Cast the frame as Bitmap object
  videoWriter.WriteVideoFrame((Bitmap)eventArgs.Frame.Clone(), elapse);
}
```

Listing 4.6: Code snippet for `videoSource_NewFrame` method.

```
public partial class MainFrame : Form {
  private static CameraConnector camConnector;
    . . .
  camConnector.StartRecording();
}

public class CameraConnector {
    . . .
  // Starts the camera recording.
  public void StartRecording() {
      . . .
    videoSource.Start();
  }
}
```

Listing 4.7: Code snippet for video recording.

```
public partial class MainFrame : Form {
    . . .
  StopEegComponent();
    . . .
  // Stops the EEG recording.
  private void StopEegComponent() {
    // Request that the worker thread stop itself:
    emoConnector.StopRecording();

    // Use the Join method to block the current thread until the object's thread terminates.
    thdEmotivConnector.Join();
  }
}

public class EmotivConnector {
    . . .
  // Prompts the tool stop capturing data from the device.
  public void StopRecording() {
    _shouldStop = true;
  }
}
```

Listing 4.8: Code snippet for stopping EEG recording.

In contrast, simply call the `StopRecording` method to stop video recording. However, there are still additional measures to add to the code in order for the program to not crash. `StopRecording` stops the current video recording and closes the video file stream. This does not mean that the connection to the camera has closed. Hence, this allows the data collector tool to have many video recordings in a single run. To properly terminate the program, `CloseConnector` must also be called. This method is invoked via the `MainFrame_FormClosed` when the user exits the tool. `CloseConnector` stops any current video recording and then sets the `videoSource` to `null`. These can be seen in Listing 4.9.

4.3.2 Parser Module

This module handles the conversion of the short story segments into a data structure for the tool. These segmented stories are represented in XML documents, as shown in Listing 4.10. The `<story>` tag serves as the root element of the XML document, with `title` and `author` as attributes. Each segment is denoted by the `<segment>` tag. The `<part>` tag represents the paragraphs in each segment.

The presentation of the segments is controlled by the `StoryNavigator`. This class is a counter that knows the current and previous segment numbers. When the user proceeds to the next segment, both counters increment by one.

```
public partial class MainFrame : Form {
    . . .
  private void MainFrame_FormClosed(object sender, FormClosedEventArgs e) {
    camConnector.CloseConnector();
  }
    . . .
  camConnector.StopRecording();
}

public class CameraConnector {
    . . .
  // Stops the camrea recording and closes the video file stream.
  public void StopRecording() {
    //Stop and free the webcam object.
    videoSource.SignalToStop();

    // Close the video file stream.
    videoWriter.Close();
  }

  // Closes the CameraConnector.
  public void CloseConnector() {
    if(videoSource.IsRunning)
      StopRecording();

    videoSource = null;
  }
}
```

Listing 4.9: Code snippet for stopping video recording.

```
<?xml version="1.0" encoding="utf-8" ?>
<story title="Man from the South" author="Roald Dahl">
  &lt;segment&gt;
     <part>It was getting on towards six o'clock so I thought I'd buy myself a beer and go out and sit in a deckchair by the swimming pool and have a little evening sun.</part>
     <part>I went to the bar and got the beer and carried it outside and wandered down the garden towards the pool.</part>
  &lt;/segment&gt;
  &lt;segment&gt;
      <part>It was a fine garden with lawns and beds of azaleas and tall coconut palms, and the wind was blowing strongly through the tops of the palm trees, making the leaves hiss and crackle as though they were on fire. I could see the clusters of big brown nuts hanging down underneath the leaves.</part>
  &lt;/segment&gt;
    . . .
  &lt;segment&gt;
      <part>This is the last segment.</part>
  &lt;/segment&gt;
</story>
```

Listing 4.10: XML representation of segmented *Man From the South* by Roald Dahl

4.3.3 Logger Module

This module contains two classes `EegLogger` and `EmotionLogger`, which implements the interface `ILogger`. `ILogger` forces the two classes to have an `Initialize` and `Log` method. The `Log` method is implemented in such a way that should there be an unexpected interruption (i.e. the program crashed), the output files are not corrupted. Each time `Log` is called, it opens the file stream, appends the contents, and closes the stream.

4.4 Data Acquisition

Figure 4.4 shows the procedural flow of the data acquisition.

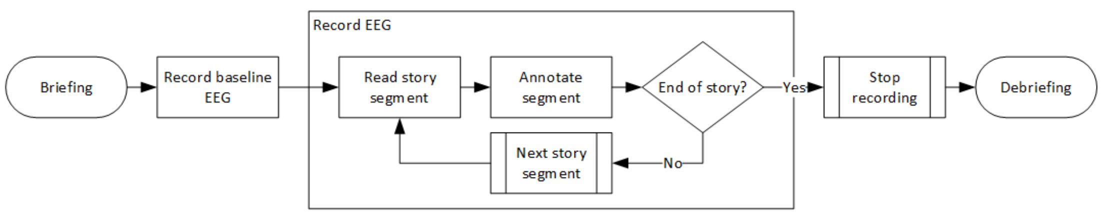


Figure 4.4: Data acquisition flowchart.

1. **Briefing.** Each participant is informed about the experiment. They are explained about the process and the definition of the labels they will annotate in each segment. They must formally grant their consent for participation in the experiment by signing the informed consent form (see Appendix B).

2. **Record baseline EEG.** The participants are then asked to close their eyes and relax for a period of two minutes while wearing the Emotiv headset. This recording serves as the baseline.

3. **Record ERP EEG.** What happens at this part is a continuous recording of EEG. The participants are to read the current story segment presented in the screen (see Figure 4.3a). After reading, they must annotate the segment (see Figure 4.3b) based on what they felt when they read it (Hourglass of Emotions model by Cambria et al. (2012)) and what do they think triggered the emotion (classification of emotions for literary response by Miall and Kuiken (2002)). This process is repeated until the last segment is reached, only then will the EEG recording stop.

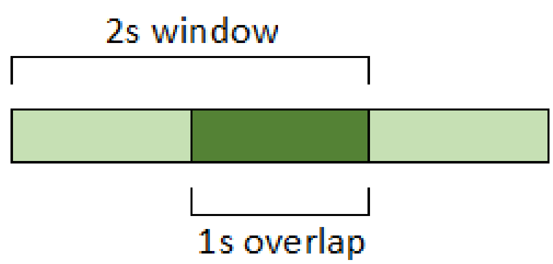
4. **Debriefing.** At this last part of the experiment, each participant is interviewed regarding what they thought of the whole process. Feedback,

comments, and suggestions regarding the data collector tool and the overall experiment itself were asked. They were also interviewed on the emotion annotations that they tagged the segments, on why they feel a segment is *striking* or on what triggered that emotion.

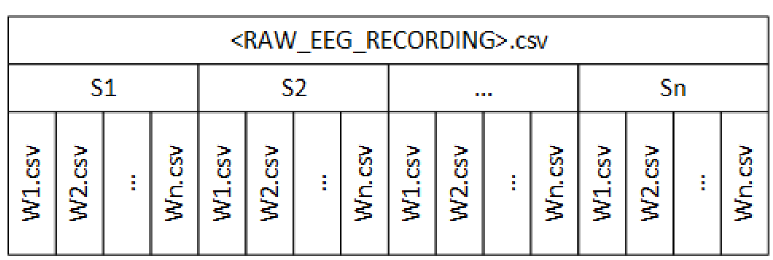
4.5 EEG Processing

4.5.1 Preprocessing

For each participant, two sets of EEG recordings were collected: the baseline and the one during the reading session. The EEG data during the reading session is first preprocessed by synchronizing and merging it with its accompanying annotations. The resulting merged file is then divided into the corresponding segments of the story, which is further divided into 2-second windows with 1-second overlap (see Figure 4.5).



(a) 2-second windows with 1-second overlap



(b) Resulting files after applying the windowing

Figure 4.5: Pre-processing for EEG data during reading session

This first part of the EEG processing is done with a program developed in C#. After this, processing for the resulting files and the baseline is the same, ergo treat the processing of the baseline and Wn.csv as the same. This part is done in MATLAB.

4.5.2 Feature Extraction

While not using the interactive interface of EEGLAB[10], this MATLAB toolbox provides the specifications of useful functions for EEG processing. EEGLAB is used as a reference and then using the default MATLAB to recreate the EEGLAB functions as needed.

According to EEGLAB, `eegfilt()` is specified as:

```
eegfilt() - (high|low|band)-pass filter data using two-way least-squares FIR
    filtering. Optionally uses the window method instead of least-squares.
    Multiple data channels and epochs supported. Requires the MATLAB Signal
    Processing Toolbox.

Inputs:
   data        = (channels,frames*epochs) data to filter
   srate       = data sampling rate (Hz)
   locutoff    = low-edge frequency in pass band (Hz)  {0 -> lowpass}
   hicutoff    = high-edge frequency in pass band (Hz) {0 -> highpass}
   epochframes = frames per epoch (filter each epoch separately
                 {def/0: data is 1 epoch}
   filtorder   = length of the filter in points
                 {default 3*fix(srate/locutoff)}
   revfilt     = [0|1] reverse filter (i.e. bandpass filter to notch
                 filter). {default 0}
   firtype     = 'firls'|'fir1' {'firls'}
   causal      = [0|1] use causal filter if set to 1 (default 0)

Outputs:
   filtwts = filter coefficients [smoothdata <- filtfilt(filtwts,1,data)]
```

Listing 4.11: eegfilt() definition

Using the specification in Listing 4.11, the creation of the delta δ, theta θ, alpha α, beta β, and gamma γ band pass filters are done with MATLAB's Filter Design and Analysis Tool[11]. This tool is accessed by calling `fdatool` in MATLAB. The creation of the filters is done by tweaking the parameters indicated in tool to match that of `eegfilt()`. The response type, design method, and magnitude specifications are the same among the different frequency band filters. The computation to get the filter order is defined in `filtorder` of Listing 4.11. The content of the frequency specifications depends on which frequency band is being created. `Fpass1` and `Fpass2` refers to the lower and upper bound frequency of the chosen frequency band (see Table 3.1 for full list). `Fstop1` and `Fstop2` is the -/+ of 0.5 to the `Fpass` values. Figure 4.6 shows creation of the delta δ band pass filter in the Filter Design and Analysis Tool.

To get the frequency bands, the output of the created filters are used as one of the parameters of `filter()`. For each band, the signals were transformed to

[10] EEGLAB, `https://sccn.ucsd.edu/eeglab/`
[11] MATLAB `fdatool`, `https://www.mathworks.com/help/signal/ref/fdatool.html`

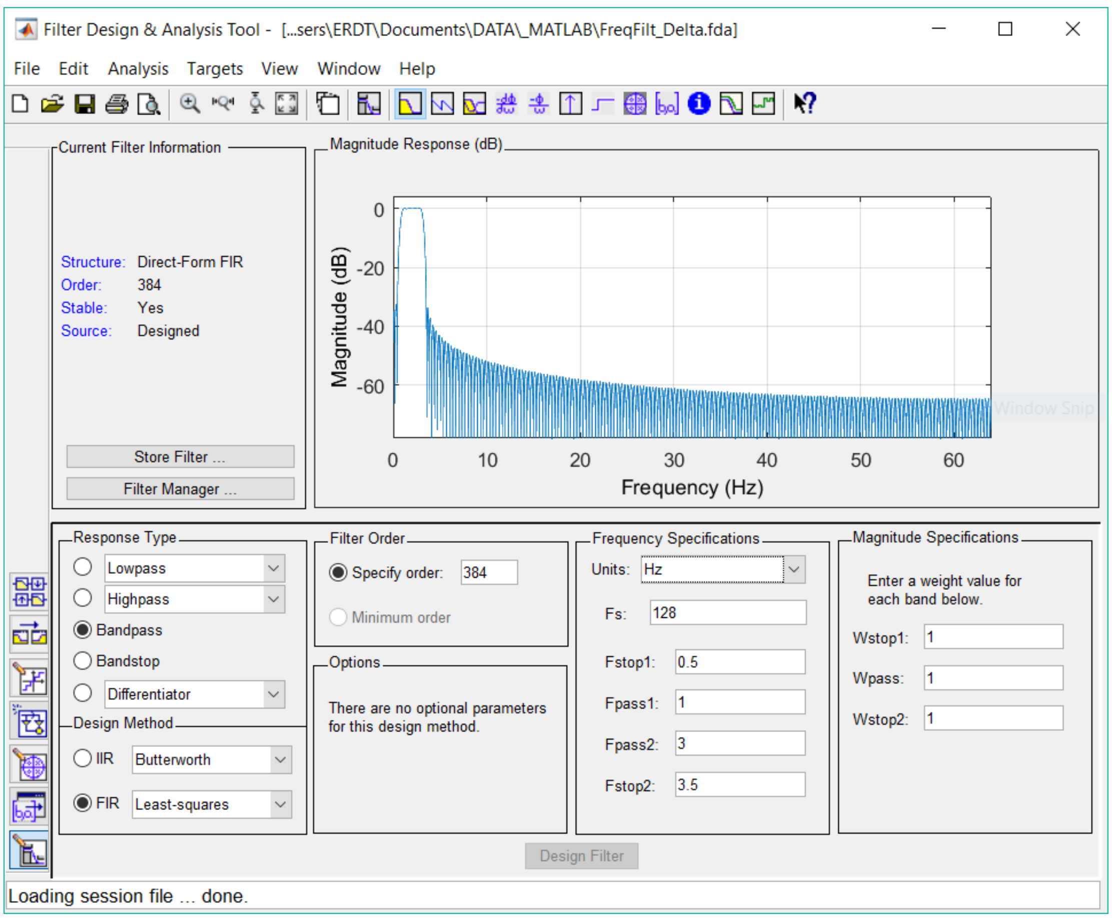


Figure 4.6: MATLAB `fdatool` session for delta δ band pass filter

the frequency domain using the Fast Fourier Transform `fft()` then the following features were extracted: peak power spectral density (PSD), peak magnitude, and mean spectral power (MSP). The PSD is a measure of a signal's power intensity. The magnitude is the absolute value of the signal. The MSP is the average of the PSD. Figure 4.7 shows the summary of the extracted features from the EEG data. For each EEG channel, there is a total of 21 features.

<EEG_CHANNEL>																				
delta			theta			alpha			beta_lo			beta_mid			beta_hi			gamma		
PM	PSD	MSP	PM	PSD	MSP	PM	PSD	MSP	PM	PSD	MSP	PM	PSD	MSP	PM	PSD	MSP	PM	PSD	MSP

Figure 4.7: Summary of features extracted from the data

Chapter 5

Findings

This chapter presents the experiments conducted as well as the observations and findings. It also discusses the issues encountered as well as the solutions

5.1 Experiment 1: Initial Data Collection and Preprocessing

The data collection tool was tested on undergraduate and graduate students of De La Salle University aged 18 and above. The short story that the participants read was *The Veldt* by Ray Bradbury, which is divided into 72 segments. In the first round of data collection from five students, it initially appeared that the tool works as it was able to capture the EEG data, emotion annotations, and video recording without the program abruptly terminating. However, a logic error was encountered when the collected data was put through the preprocessing phase.

The error was located at the line of code for logging the timestamp. This error is peculiar because it works in the `EegLogger` while it doesn't in `EmotionLogger` despite the fact they use the same function. In `EmotionLogger`, the program takes note of the time the participant annotates the emotions because this time period will be removed from the ERP EEG recording. Listing 5.1 shows the logical error where this occurred. The output for those logged in `EegLogger` is something like `1468300340536.31`. Those in `EmotionLogger` looks like `1.4683E+12`.

This seemingly minor error was resolved by simply converting the `double` value timestamp to `string` before storing it in the variable as shown in Listing 5.2. However, the effect of this error was that the data collected from those five

```
// Method for getting the timestamp.
public static double GetCsvTimestamp();

// Usage in EegLogger
eeglog.Log(GetCsvTimestamp(), <otherParameters>);

// Usage in EmotionLogger
startTime = GetCsvTimestamp();
  . . .
endTime = GetCsvTimestamp();
emoLog.Log(startTime, endTime, <otherParameters>);
```

Listing 5.1: Logic error in code for logging timestamp.

```
startTime = GetCsvTimestamp().ToString();
  . . .
endTime = GetCsvTimestamp().ToString();
emoLog.Log(startTime, endTime, <otherParameters>);
```

Listing 5.2: Resolution to timestamp logging logic error.

participants are unusable. They cannot repeat the experiment unless they read a different story.

Another round of data collection was gathered from two students. At this point, the tool was producing the expected output files from it. These data were put through the preprocessing module where the final output are the extracted features. The next phase is building the datasets and training and evaluating the reader affect model.

5.2 Initial Findings

Below are the consolidated responses from the participants during their debriefing regarding their experiences with the experiment. It goes over their thoughts on their reading experience, their emotional responses, and on software usage.

5.2.1 Reading Experience and Emotional Response

The way position in which they were reading the story may have a slight effect as that is not how they are used to. However, the presentation of the story via the tool was no problem for them. The environment may also have an impact as some are used to have minimal lighting when reading and some find noise a bit distracting. A slight discomfort in wearing the headset was a common complaint among the participants. They note that the longer they wear the headset, the more they feel the two nodes in front pressing on their foreheads. For some, they became used to the discomfort, while for others, it became a slight distraction.

When asked which classification was the most prevalent in triggering their emotional response, all participants said that it was due to the plot and characters of the story (narrative feelings). This was followed by their overall enjoyment or satisfaction in reading the segment (evaluative feelings).

5.2.2 Software Usage

Their response on the usage of the tool was generally positive. Some have noted that the segmentation of the story seemed geared towards creating suspense. Nevertheless, each segment were coherent and sufficient by itself. The annotation of the emotions becomes tedious later on. They said that tagging emotions was not a problem for the minor or transitional segments but then becomes a bit troublesome on the high intensity parts such as the climax. This is because they want to read the next part but they have to annotate first before proceeding to the next segment.

All participants have expressed a common concern with regards to the definition of the Hourglass of Emotions dimensions. Halfway through the experiment, some have forgotten what *Sensitivity* or *Aptitude* covers. This is why they note that the emojis were helpful indicators. A possible resolution to this is to (a) show the participants a screenshot of the annotation part of the tool (see Figure 4.3b) and (b) provide a more in-depth explanation of the Hourglass of Emotions dimensions and its relation to the emojis.

Appendix A

Research Ethics Forms and Checklists

RESEARCH ETHICS CLEARANCE FORM[1] For Thesis Proposals
Names of Student Researcher(s): Kristine Ma. Dominique F. KALAW
College: College of Computer Studies
Department: Software Technology
Course: Master of Science in Computer Science
Expected Duration of the Project: from: January 2016 to: April 2017
Ethical considerations *(The Ethics Checklists may be used as guides in determining areas for ethical concern/consideration)*
To the best of my knowledge, the ethical issues listed above have been addressed in the research. Ethel Chua Joy ONG _________________________________ **Name and Signature of Adviser/Mentor:** **Date:**
Noted by: _________________________________ **Name and Signature of the Department Chairperson:** Dr. Rafael A. CABREDO **Date:**

[1] The same form can be used for the reports of completed projects. The appropriate heading need only be used.

DE LA SALLE UNIVERSITY
General Research Ethics Checklist

This checklist is to ensure that the research conducted by the faculty members and students of De La Salle University is carried out according to the guiding principles outlined in the Code of Research Ethics of the University. The investigator is advised to refer to the De La Salle University Code of Research Ethics and Guide to Responsible Conduct of Research before completing this checklist. Statements pertinent to ethical issues in research should be addressed below. The checklist will help the researcher/s and advisers/readers/evaluators determine whether procedures should be undertaken during the course of the research to maintain ethical standards. The University's Guide to the Responsible Conduct of Research provides details on these appropriate procedures.

Faculty/ASF Researcher Details	
Principal Investigator	Kristine Ma. Dominique F. KALAW
Department	College of Computer Studies Software Technology Department
Proposed Title of the Research	Recognizing Reader's Affect Using EEG Data
Term(s) and academic year in which research is to be conducted	AY2015-2016, T2-T3; AY2016-2017, T1-T3
Other researchers involved in project including their positions (e.g., student, faculty)	

Student Researcher Details (for students who are co-proponents)	
Course Title	N/A
Department	N/A
Thesis Adviser	Ethel Chua Joy ONG
Email Address	ethel.ong@delasalle.ph

This checklist must be completed AFTER the **De La Salle University Code of Ethics** ***has been read and BEFORE gathering data.***

Questions	Yes	No
1. Does your research involve human participants (this includes new data gathered or using pre-existing data)? If your answer is **yes**, please answer **Checklist A (Human Participants).**	✓	
2. Does your research involve animals (non-human subjects)? If your answer is **yes**, please answer **Checklist B (Animal Subjects).**		✓
3. Does your research involve Wildlife? If your answer is **yes**, please answer **Checklist C (Wildlife)**.		✓
4. Does your research involve microorganisms that are infectious, disease causing or harmful to health? If your answer is **yes**, please answer **Checklist D (Infectious Agents).**		✓
5. Does your research involve toxic/chemicals/ substances/materials? If your answer is **yes**, please answer **Checklist E (Toxic Agents).**		✓

Research with Ethical Issues to address:

If you have a YES answer to any of the above categories, you will be required to complete a detailed checklist for that particular category. A YES answer does not mean the disapproval of your research proposal. By providing you with a more detailed checklist, we ensure that the ethical concerns are identified so these can be addressed in adherence to the University Code of Ethics.

Declaration of Conflict of Interest

[✓] 1. I do not have a conflict of interest in any form (personal, financial, proprietary, or professional) with the sponsor/grant-giving organization, the study, the co-investigators/personnel, or the site.

[ ] 2. I do have a conflict of interest, specifically:

[ ] A. I have a personal/family or professional interest in the results of the study (family members who are co-proponents or personnel in the study, membership in relevant professional associations/organizations).

Please describe the personal/family or professional interest:

____

____

____

[ ] B. I have propriety interest vested in this proposal (with the intent to apply for a patent, trademark, copyright, or license)

Please describe propriety interest:

____

____

____

[ ] C. I have significant financial interest vested in this proposal (remuneration that exceeds P250,000.00 each year or equity interest in the form of stock, stock options or other ownership interests).

Please describe financial interest:

____

____

____

Declaration

I certify that I have read and understood the De La Salle University Code for the Responsible Conduct of Research and will abide by the ethical principles in this document. To the best of my knowledge that my research proposal does not involve any of the above-mentioned categories. I will submit a final report of the proposed study to the DLSU-Research Ethics Office. I will not commence with data collection until I receive an ethics review approval from the College Research Ethics Committee.	
Kristine Ma. Dominique F. KALAW **Name and Signature of Principal Investigator**	**Date**

FOR GRADUATE and UNDERGRADUATE DLSU STUDENTS ONLY		
I confirm that the student(s) is/are capable of undertaking this research in a safe and ethical manner.		
Ethel Chua Joy ONG Adviser's Name	Signature	Date

DE LA SALLE UNIVERSITY

Checklist A

Research Ethics Checklist for Investigations involving Human Participants

This checklist must be completed ***AFTER the*** **De La Salle University Code of Research Ethics and Guide to Responsible Conduct of Research** ***has been read and BEFORE gathering data****. The University Code of Research Ethics is available at* [***http://www.dlsu.edu.ph/offices/urco/forms/URCO-Code-of-Research-Ethics_August2011.pdf***](http://www.dlsu.edu.ph/offices/urco/forms/URCO-Code-of-Research-Ethics_August2011.pdf)

NOTE: This checklist is completed after the research proponent fills out the General Checklist Form.

Only answer this Checklist if you answered YES on question 1 of the General Checklist.

Researcher Details	
Lead Researcher's Signature	
Lead Researcher's Name (Please Print)	Kristine Ma. Dominique F. KALAW
Email Address(es)	kristine_ma_kalaw@dlsu.edu.ph
Department/College	College of Computer Studies Software Technology Department
Proposed Title of the Research	Recognizing Reader's Affect Using EEG Data
Term(s) and academic year in which research project is to be undertaken	AY2015-2016, T2-T3; AY2016-2017, T1-T3
Other faculty members involved in project and their department affiliation(s)	Ethel Chua Joy ONG Thesis Adviser AdRIC Director

Provide a brief description of the data collection procedure to be undertaken in the research: The participants will wear an EEG headset while they read a short story that is divided into segments. Before proceeding to the next segment, they will have to annotate the emotions they felt for the segment. An interview is also conducted after the reading session.

The following should be attached to the checklist:
• A copy of the informed consent form to be used in the study. • A copy of the instrument/tool that will be administered to the participants. • If applicable, a copy of the letter seeking permission to collect data from participants who are under the supervision of an agency, institution, department, or office. • If applicable, a copy of the parental consent form for participants below 18 years old.

The following items refer to important ethical considerations in the conduct of research with human participants. Provide a check for the appropriate answer to each question.

Source of data *Please check all that apply:*		
	1. New data will be collected from human participants If you checked this item, how will the new data be gathered? Please check all that apply. **After answering this question, please proceed to page 3**	
	✓	**Experimental Procedures/Intervention/ Treatments**
		Focus Group
	✓	**Personal Interviews**
	✓	**Self-administered Questionnaire**
		Researcher-administered Questionnaire
		Internet survey
	✓	**Observation**
		Telephone survey
	✓	**Others, please specify:** Video recording, audio recording
	2. Pre-existing data from human participants, i.e., from a dataset **If you checked this item, please proceed to page 7**	

If both options are checked (both new data and pre-existing data), **answer all of the questions in this document.**

Only answer if new data will be collected (item 1 above)	
Sampling Details	
Number of Participants/Subjects	at least 30 participants
Location where the participants will be recruited/ where subjects will be obtained?	De La Salle University
How long will the data collection take place?	Jan 2017 - Feb 2017
Who will perform the data collection?	Kristine Ma. Dominique F. KALAW
Location(s) where data collection will take place	De La Salle University
What procedures will be employed to ensure voluntary consent from participants?	Meals will be provided.
Data Retention	
How long will data with participant identifiers be kept after the publication of the first paper from the project?	Participants are given the option to include or have their name be anonymous as indicated in the attached informed consent form.
How long will anonymized data be kept after the publication of the first paper from the project?	Participants are given the option to have their data only be used for this specific research or also be used for future studies as indicated in the attached informed consent form.
Procedure for Informed Consent	
How will informed consent be recorded? (check all that applies) Reminder: please attach informed consent that will be used in the study	[✓] Written Consent [ ] Audio-recorded Consent [ ] Online/Email recorded Consent [ ] Others, please specify:

If you will not obtain a recorded informed consent, answer the questions that follow:

Why does the waiver of informed consent not pose a threat to the welfare and rights of the participants?

Why is recording an informed consent not practical for the proposed study?

	Yes	No	Not Applicable
1. Will the research involve students who will be receiving course credits for their participation? **If YES, please attach a copy of the consent form and a summary of the debriefing process that will help participants understand how their participation in the research has provided a relevant learning experience to the crediting course.**	☐	☑	☐
2. Does the study involve participants below 18 years old or those who are unable to give their informed consent? **If YES, please attach a copy of the parental consent form.**	☐	☑	☐
3. Is there a possibility that the research can induce physical and/or psychological harm to the participants? Will they experience pain or some discomfort as a result from their participation in the research? **If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.**	☐	☑	☐
4. Will the participants be deliberately falsely informed or made unaware that they are being observed? Will they be misled in a way that they will possibly object to or show unease when told of the real purpose of the study? **If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.**	☐	☑	☐
5. Will the research involve the discussion of, or questions on, sensitive topics (e.g. sexual activity, substance abuse, or mental health)? **If YES, please make sure that the informed consent form explicitly states that sensitive questions will be posed and that you will safeguard the anonymity of the participants and ensure confidentiality. Please attach a copy of your informed consent form and your instrument.**	☐	☑	☐

	Yes	No	Not Applicable
6. Will the research involve the administration of drugs, or other substances to the participants? **If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.** **Please also attach a description of the procedure that will ensure that the participants will be brought back to their physical and psychological states prior to their participation in the research.**	☐	☑	☐
7. Will biological samples (e.g. blood, saliva, urine) be obtained from the participants? **If YES, will this involve invasive procedures? Please attach a description of these procedures.**	☐	☑	☐
8. Will genetic materials be obtained from the biological samples? **If YES, please attach a description of the procedures that will ensure confidentiality. Please attach the informed consent form.**	☐	☑	☐
9. Will financial inducements (other than reasonable expenses, like transportation or meal allowances) be offered to the participants for their participation in their research? **If YES, the researcher(s) should be mindful of how the inducements can influence the participants' responses or behaviors during the research. Indicate the financial inducements offered to the participants:** ____	☐	☑	☐
10. Is there a possibility for groups or communities to be harmed by the dissemination of the research findings? **If YES, please attach a description of procedures to ensure the anonymity and confidentiality of the research findings.**	☐	☑	☐

Answering <u>YES</u> to most of the above items will signal an ethical issue that needs to be addressed. Some actions that will allow adherence to research ethical principles are provided with each item. The researcher is advised to refer to the University's Guide to the Responsible Conduct of Research for the appropriate procedures to ensure adherence to ethical principles in the conduct of research.

<u>Declaration</u>

I certify that I have read and understood the De La Salle University Code for the Responsible Conduct of Research and will abide by the ethical principles in this document. I will submit a final report of the proposed study to the DLSU-Research Ethics Office. I will not commence with data collection until I receive an ethics review approval from the College Research Ethics Committee.

Kristine Ma. Dominique F. KALAW **Name and Signature of Principal Investigator**	**Date**

FOR GRADUATE and UNDERGRADUATE DLSU STUDENTS ONLY

I confirm that the student(s) is/are capable of undertaking this research in a safe and ethical manner.

Ethel Chua Joy ONG Adviser's Name	Signature	Date

FOR PROPONENTS WHO WILL GATHER NEW DATA ONLY, PLEASE STOP ANSWERING.

Use of Pre-existing Data collected from Human Participants		
Indicate the dataset from which the data for the study will be sourced		
Is the data publicly available, i.e., the access to which does not necessitate an approval process?		Yes Please indicate where the dataset is available:
		No Please indicate/attach the approval authority for access:
Was the original dataset originally collected for the present study's purpose?		Yes **Please attach the Consent Form used in the original study.**
		No **Please attach the Information Collection Statement (i.e., the statement given to informants providing them with the rationale for the collection of specific information).**
Does the original data set contain sensitive data, that is information that an individual would not likely want to be disclosed publicly, e.g., data on sexual activities, substance use?		Yes **Please describe the type of sensitive data to be used in the present research:**
		No
Does the original dataset have personal identifiers?		No *(This means that neither the researcher nor the participant provided any personal identifiers)*
		Yes, specifically: ______ Direct *(i.e., the participant provided personal details like name and address)* _____ Indirect (*i.e., the participant was given a respondent code to make the participant identifiable)*
Will new data be collected and analyzed along with data from the existing dataset?		Yes **Please answer questions on page 3-5.**
		No

Declaration

I certify that I have read and understood the De La Salle University Code for the Responsible Conduct of Research and will abide by the ethical principles in this document. I will submit a final report of the proposed study to the DLSU-Research Ethics Office. I will not commence with data collection until I receive an ethics review approval from the College Research Ethics Committee.

______________________________ **Name and Signature of Principal Investigator**	______________ **Date**

FOR GRADUATE and UNDERGRADUATE DLSU STUDENTS ONLY
I confirm that the student(s) is/are capable of undertaking this research in a safe and ethical manner.
________________ Adviser's Name ________________ Signature __________ Date

Appendix B

Informed Consent Form

De La Salle University
College of Computer Studies

RESEARCH INFORMATION SHEET (VERSION-JULY 11, 2016)

You are being asked to participate in a research entitled,

RECOGNIZING READER'S AFFECT USING EEG DATA

You must be 18 years or older to participate in this study. Your participation is voluntary. Please carefully read the information below and do not hesitate to ask any questions regarding the experiment that may not be clear to you.

This study is conducted by Kristine Ma. Dominique F. Kalaw, supervised by Prof. Ethel Chua Joy Ong, as part of her work towards a Master's degree in Computer Science at De La Salle University.

A. INTRODUCTION/PURPOSE

This study aims to associate brainwave patterns to specific emotions while reading literary fiction.

B. PROCEDURE

You are asked to read at least two (2) short stories. One session involves reading one story in a single sitting. The second session may not necessarily be immediately after the first. Each session will last approximately 1 hour and 30 minutes. If you agree to participate in this research, this would imply the following:

1. During the session, you will wear an Emotiv Insight headset to measure and capture your brain activity. While wearing the headset, hair ornaments or accessories should be removed.
2. A camera will be used to record the whole session.
3. Prior to reading the story, a baseline of your brain activity will be recorded. You are asked to close your eyes and be as relaxed and as comfortable as possible for a period of two (2) minutes.
4. You will be asked to read the pre-selected short story, which is presented in segments, using the software developed by the researcher. Please note that you may not go back to previous segments. Only the immediate previous segment of the current segment is displayed for your reference.
5. For each current segment, you will identify the degree of *pleasantness*, *attention*, *sensitivity*, and *aptitude* it causes you. You will also indicate if whether the segment has struck you or caught your attention. Lastly, you will indicate whether the emotion you are experiencing is an evaluative feeling, narrative feeling, aesthetic feeling, or others. All this is done using the software developed by the researcher.
6. Steps 4 and 5 are repeated until you have finished the story.
7. After, you will answer a participant profile questionnaire as well as have a short interview about the experience. Both of these are used as part of the data collected from you. Please note that the short interview will be voice-recorded.

C. POTENTIAL RISKS AND DISCOMFORT

The Emotiv Insight is a 5-channel, wireless EEG headset that records your brainwaves. It is a commercial product marketed worldwide and is designed for everyday use. It uses a polymer sensor that is safe to use and offers great electrical conductivity with the convenience of a dry sensor. These sensors read the brainwave signals and then transmits these signals to a computer via Bluetooth.

This device has global recognition for its personal usage such as assessing athletic performance, cognitive training, or health and well-being (*Source: http://emotiv.com/insight/*). The technology is also backed and trusted by the scientific, academic, engineering and media communities and has been validated by many independent research papers (*Source:* *http://emotiv.com/the-science/*).

EEG or brainwave recording procedures are quite safe and has been in use for over 30 years; it is used routinely in hospitals to test brain function and to diagnose illness such as temporal epilepsy. There are no known major risks associated with this procedure other than a mild discomfort for some people who have sensitive skin when wearing the headset. This is not permanent and is of no serious consequence (*Source:* *https://emotiv.zendesk.com/hc/en-us/articles/204701495-EEG-Basic-Participant-Information-and-Safety*). However, if you find the headset uncomfortable to use or if you decide to stop the session for any other reason, the experiment will be halted immediately.

D. POTENTIAL BENEFIT TO SUBJECTS AND/OR TO SOCIETY

Apart from some personal insights with regards to your awareness of your emotions during the reading process, you will not directly benefit from your participation in this research study.

Since the study will attempt to associate brainwave patterns to specific emotions while reading literary fiction, the results of this study would provide a useful baseline data for studies involved in reader-response or emotion theory, or may serve as reference for future EEG-based affect recognition studies.

E. CONFIDENTIALITY

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or as required by law. The information collected about you will be coded using a fake name (pseudonym) or initials and numbers. The information which has your identifiable information will be kept separately from the rest of your data. All the information collected will be stored in a private archive.

The EEG recordings of your sessions will be used solely for experimental purposes, and after the data collection is over, they will be stored in a private archive. Portions of these EEG recordings may be published and/or presented in scientific journals and/or scientific conference proceedings, but will never be published in a non-scientific venue. Further, no information, such as name, address, or other private information, will be included in these publications. Likewise, for this research, your video and voice recordings will be used solely for analysis and gathering insights regarding the experiment. It will also be stored in a private archive.

Apart from this possible usage, such data will only be viewed/used for experimental purposes. At any time during or after the experiment, you may request to review or edit the tapes and/or request that your files be destroyed.

F. PARTICIPATION AND WITHDRAWAL

Your participation in this study is completely voluntary. If at any point in time you wish to withdraw during or after the experiment, you may do so without penalty or consequence of any kind. Any data collected, should you withdraw, will be disposed properly.

G. IDENTIFICATION OF RESEARCHER

If you have any questions or concerns about the research, please feel free to contact:

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CONSENT TO PARTICIPATE IN "RECOGNIZING READER'S AFFECT USING EEG DATA"

I, the undersigned, confirm that (please tick the appropriate boxes):

	TAKING PART IN THIS PROJECT	
1.	I have read and understood the information about the research as provided in the Information Sheet dated July 11, 2016.	☐
2.	I have been given the opportunity to ask questions about the study and my participation.	☐
3.	I voluntarily agree to participate in the study and am aware that taking part in it includes being interviewed and voice-recorded.	☐
4.	I understand that my taking part is voluntary; I can withdraw from the study at any time and I do not have to give any reason for why I no longer want to take part.	☐
	USE OF THE INFORMATION I PROVIDE FOR THIS PROJECT ONLY	
5.	The procedures regarding confidentiality have been clearly explained to me.	☐
6.	Select only **one** of the following:	
	a. I would like my name used and understand that what I have said or written as part of this study will be used in reports, publications, and other research outputs so that anything I have contributed to this research can be recognized	☐
	b. I would like to remain anonymous.	☐
	USE OF THE INFORMATION I PROVIDE BEYOND THIS PROJECT	
7.	I agree for the data I provide be archived by the researchers.	☐
8.	Select only **one** of the following:	
	a. I am allowing other researchers to have access to this data if they agree to preserve the confidentiality of the data and if they agree to the terms I have specified in this form.	☐
	b. I am **not** allowing other researchers to have access to this data and consent only of its use to this project.	☐
9.	If you are **allowing** other researchers to have access to this data (**8a**), select the type/s of data you consent for the other researchers to use. Skip this item if you are **not allowing** other researchers to have access to this data (**8b**). ☐ EEG recording ☐ Video recording ☐ Voice recording	
	SO THAT THIS STUDY CAN USE THE INFORMATION I PROVIDE LEGALLY	
10.	I agree to assign the copyright I hold in any materials related to this project to the Researcher.	☐

PARTICIPANT:

Name of Participant	Signature	Date

RESEARCHERS:

KRISTINE MA. DOMINIQUE F. KALAW Name of Researcher	Signature	Date
ETHEL CHUA JOY ONG Name of Researcher	Signature	Date

Appendix C

Sample Segments of Selected Short Stories

The Veldt by Ray Bradbury

Segment #1

"George, I wish you'd look at the nursery."

"What's wrong with it?"

"I don't know."

"Well, then."

"I just want you to look at it, is all, or call a psychologist in to look at it."

"What would a psychologist want with a nursery?"

"You know very well what he'd want." His wife paused in the middle of the kitchen and watched the stove busy humming to itself, making supper for four.

"It's just that the nursery is different now than it was."

"All right, let's have a look."

Segment #2

They walked down the hall of their soundproofed, Happy-life Home, which had cost them thirty thousand dollars installed, this house which clothed and fed and rocked them to sleep and played and sang and was good to them. Their approach sensitized a switch somewhere and the nursery light flicked on when they came within ten feet of it. Similarly, behind them, in the halls, lights went on and off as they left them behind, with a soft automaticity.

Segment #3

"Well," said George Hadley.

They stood on the thatched floor of the nursery. It was forty feet across by forty feet long and thirty feet high; it had cost half again as much as the rest of the house. "But nothing's too good for our children," George had said.

Segment #4

The nursery was silent. It was empty as a jungle glade at hot high noon. The walls were blank and two dimensional. Now, as George and Lydia Hadley stood in the center of the room, the walls began to purr and recede into crystalline distance, it seemed, and presently an African veldt appeared, in three dimensions, on all sides, in colors reproduced to the final pebble and bit of straw. The ceiling above them became a deep sky with a hot yellow sun.

Segment #5

George Hadley felt the perspiration start on his brow.

"Let's get out of this sun," he said. "This is a little too real. But I don't see anything wrong."

"Wait a moment, you'll see," said his wife.

Man from the South by Roald Dahl

Segment #1

It was getting on towards six o'clock so I thought I'd buy myself a beer and go out and sit in a deckchair by the swimming pool and have a little evening sun.

I went to the bar and got the beer and carried it outside and wandered down the garden towards the pool.

Segment #2

It was a fine garden with lawns and beds of azaleas and tall coconut palms, and the wind was blowing strongly through the tops of the palm trees, making the leaves hiss and crackle as though they were on fire. I could see the clusters of big brown nuts hanging down underneath the leaves.

Segment #3

There were plenty of deck-chairs around the swimming pool and there were white tables and huge brightly coloured umbrellas and sunburned men and women sitting around in bathing suits. In the pool itself there were three or four girls and about a dozen boys, all splashing about and making a lot of noise and throwing a large rubber ball at one another.

Segment #4

I stood watching them. The girls were English girls from the hotel. The boys I didn't know about, but they sounded American, and I thought they were probably naval cadets who'd come ashore from the U.S. naval training vessel which had arrived in harbour that morning.

Segment #5

I went over and sat down under a yellow umbrella where there were four empty seats, and I poured my beer and settled back comfortably with a cigarette.

It was very pleasant sitting there in the sunshine with beer and cigarette. It was pleasant to sit and watch the bathers splashing about in the green water.

The Fisherman and the Jinni from *One Thousand and One Nights*

Segment #1

It is said, oh wise and happy King, that a very poor fisherman who swore by Almighty God that he would only cast his net three times each day, went down to the sea late one afternoon as usual, waited until he saw the moon shining above him, and then threw his net very carefully into the water.

Segment #2

He sat there for a time, and then, when he pulled on his net and felt that it had grown heavy, he sang to himself:

"Glide over to me, my magnificent fish

And slither into my waiting net

So that someone asleep on his soft silken bed

Will awaken and buy you with his silver bread."

Segment #3

He opened his net and there, to his horror, found a dead donkey. "A donkey?" he cried out. "My wretched luck. You send me a donkey when you know that my family and I are starved out of our brains?" He managed to free it from his net with one hand while pinching his nose with the other to block out the horrible smell.

Segment #4

He cast his net carefully into the sea again, waited for it to sink, tugged on it and to his amazement felt that the net was even heavier than the first time. It was so heavy he had to climb back on to the shore, drive a stake into the ground, and tie the rope of the net to the stake. Then he hauled with all his might until he managed to pull the net up out of the sea.

Segment #5

But instead of an abundance of fish jumping and playing in the net he found a broken, rusty wooden chest filled with sand. He shouted in a loud voice, "A chest? Is this how you compensate my work? My labour? Or are you telling me that the key to my good fortune lies inside this coffin?"

He kicked the chest as hard as he could, but then managed to recover his patience, and washed out his net once again.

Appendix D

Resource Persons

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