University of Essex

School of Computer Science and Electronic Engineering (CSEE)

CE901 Dissertation

Multi-Motions (Heart-Rate)

Allan Thomas
2214569

Supervisor: **Dr Caterina Cinel**

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Abstract

To tackle the challenges in the field of Artificial Emotional Intelligence, this thesis on "Multi-Motions" focuses on developing a comprehensive approach. This involves using ultra-short-term Heart Rate Variability measures for real-time emotional state recognition, integrating various physiological signals, and creating a desktop application for enhanced emotion recognition. The research aims to overcome obstacles in sensor technology, ensure signal accuracy, and accurately interpret emotional states.

Acknowledgment's

I wish to thank Dr Caterina Cinel for being my supervisor for this project and I would also like to thank Dr Vito De Feo for providing the .csv files for the heart rate dataset. She was also crucial in helping me get to the point where I can now declare that, hopefully, I will earn a degree.

Contents

CHAPTER 1

Introduction

Heart rate variability (HRV) has become a crucial metric in the dynamic field of psychophysiology to investigate emotional arousal, particularly with regard to online and mobile applications. This line of research emphasizes the significant impact of emotions on human behavior and cognitive function. Its roots are in foundational theories that date back to seminal works in 1995. Interestingly, HRV provides a window into understanding these emotional impacts, as it is a reflection of activity in the autonomic nervous system. It is impossible to overestimate the importance of HRV in this situation because it offers a direct, non-invasive way to measure physiological reactions linked to a variety of emotional states. Recent developments in sensor technology have played a major role in the breakthrough of HRV analysis. Advances in technology have enabled the non-invasive collection of heart rate data, which opens the door to real-time emotional arousal analysis and interpretation. This study explores the potential of HRV beyond conventional applications, with a focus on the technology. By exploring HRV's time and frequency domain features, the study seeks to expand on our understanding of HRV and its application to emotional state recognition. As part of the investigation, the usefulness of ultra-short term HRV measures is assessed, which potentially extends and challenges the accepted standards of HRV analysis. Although the study takes into account other physiological signals, like pupil size, galvanic skin response, and facial expressions, its main focus is still on the subtleties of the heart rate and HRV data. The development of an advanced classification/regression model meant for in-the-moment emotion detection depends on these parameters. Through the model's integration of these various physiological signals, an all-encompassing desktop application will be created, improving the accuracy of emotion recognition in the context of Artificial Emotional Intelligence (AEI). To put it briefly, the goal of this research is to provide a comprehensive and nuanced understanding of how heart rate and HRV data, when combined with other physiological markers, can aid in the real-time and accurate assessment of emotional states. It has the potential to significantly advance psychophysiology, especially in the creation of instruments and techniques for assessing emotional arousal via heart rate variability in a range of settings, such as wearable and mobile technologies.

1.1 Problem Definition

The research aims to investigate and enhance the precision of real-time emotion recognition using heart rate variability (HRV) and other physiological signals, contributing to the field of Artificial Emotional Intelligence (AEI). The specific challenges addressed include:

Exploring the Efficacy of Ultra-Short Term HRV Measures: Traditional norms typically rely on longer periods for HRV analysis. This study challenges these norms by investigating the potential of shorter periods for HRV analysis in the context of emotional arousal and state recognition.

Developing a Classification/Regression Model: The goal is to create a model that integrates multiple physiological indicators, including HRV, facial expressions, galvanic skin response, pupil size, and heart-rate data. This model aims to predict emotional valence and arousal in real-time and analyze the relationship between various physiological signals and emotional states.

Creation of a Desktop Application: The research seeks to develop a desktop application that can predict emotional states and provide insights into how physiological responses are linked to emotional experiences. This application is intended to be used in various domains, potentially impacting learning, memory, and interactive gaming.

Advancing Sensor Technology Utilization: The study leverages recent advancements in sensor technology for the non-intrusive collection and real-time analysis of physiological data, enhancing the understanding of the interplay between physiological signals and emotional responses.

The thesis represents a significant effort to contribute to the field of AEI by offering a validated model for predicting emotional states and providing insights into the relationship between physiological signals and emotional experiences.

1.2 Scope

The main goal of the thesis was: -

To investigate and enhance the precision of real-time emotion recognition using HRV and other physiological signals, contributing to the field of Artificial Emotional Intelligence.

To explore the efficacy of ultra-short term HRV measures in the context of emotional arousal and state recognition.

To develop a classification/regression model that integrates multiple physiological indicators, including HRV, facial expressions, galvanic skin response, pupil size, and heart-rate data.

To create a desktop application that can predict emotional valence and arousal in real-time and analyze the relationship between various physiological signals and emotional states.

To offer a validated model for predicting emotional states, with insights into how physiological responses are linked to emotional experiences, potentially impacting learning, memory, and interactive gaming domains.

To leverage recent advancements in sensor technology for the non-intrusive collection and real-time analysis of physiological data.

The limitation of this thesis is: -

Sample Size and Diversity: If the study used a limited or homogenous sample, this could affect the generalizability of the findings. The extent to which the results can be applied to different populations may be limited.

Methodological Constraints: The specific methods used for data collection and analysis may have inherent limitations. For example, the use of certain software, tools, or algorithms might have specific constraints that could impact the results.

Sensor Accuracy and Consistency: Since the study relies on sensor technology for collecting physiological data, any limitations in sensor accuracy or consistency can affect the reliability of the data.

Controlled Environment: If the data collection occurred in a controlled environment, this might not accurately reflect real-world scenarios where environmental variables are less predictable.

Short-term Analysis: The focus on ultra-short-term HRV measures, while innovative, might have limitations compared to longer-term analysis, which could provide a unique perspective on emotional arousal and state recognition.

Technical Challenges: The development and integration of a complex classification/regression model and a desktop application could face technical challenges, such as software limitations, integration issues, or computational constraints.

Interpretation of Emotional States: The interpretation of physiological signals as emotional states is inherently complex and subjective. The research might face challenges in accurately mapping these signals to specific emotional states due to the subjective nature of emotions.

Potential Biases in Data or Analysis: Any biases in the dataset or during the analysis phase can lead to skewed results. This includes selection bias, confirmation bias, or biases introduced during data processing.

1.3 Bio-Signals

1.3.1 Heart Rate

Integration with iMotions: iMotions has the capacity to synchronize ECG data, offering insights into heart rate variability (HRV), a critical concept for comprehending stress and emotional arousal.

Application: Emotional states, stress levels, and relaxation levels can all be inferred from HRV data. iMotions may use heart rate interval variability analysis to make associations with various emotional states.

1.3.2 Galvanic Skin Response (GSR)

Integration in iMotions: Another important physiological metric that iMotions can incorporate is GSR, which represents variations in skin conductance brought on by perspiration.

Application: Given that increased sweating is a common reaction to excitement, tension, or anxiety, it is especially helpful in evaluating arousal. GSR data can be used by iMotions to gauge how strongly an emotion is being felt.

1.3.3 Facial Expression Analysis (FER)

Integration with iMotions: iMotions uses computer vision techniques to track and interpret face movements, enabling advanced facial expression analysis.

Application: This is used to read different emotional states from facial expressions. With the program, one may discern minute variations in facial muscles that reveal a person's emotional condition.

1.3.4 Pupil Size Analysis

Integration with iMotions: One aspect of eye tracking technology that iMotions uses is pupil size measuring.

Application: Variations in pupil size may be a sign of emotional and cognitive stress. Pupil dilation in reaction to various stimuli can be analyzed by iMotions, providing insights into emotional and cognitive processes.

1.4 Work Undertaken

Over the course of the thesis several achievements were made. They were:

Creating a custom emotion recognition model for the .csv files provided by Dr. Vito de feo.

Created a code to visualize heart rate and also plotted a graph from scratch using python and matlab.

Implemented several optimization techniques such as removing the missing values from the dataset and using interpolation to fill them, thereby visualizing the data more accurately.

Extracted two unique features RMSSD and SDNN from the dataset and plotted the graph for it.

The result was that the model could process the emotions from the dataset accurately and visualize them by plotting the graph with precision.

1.5 Structure of the work

"The rest of the paper is structured as follows: Chapter 2 delves into the exploration of emotional arousal through heart rate variability (HRV) in online applications, encompassing a literature review that spans foundational theories, technological advancements, and the circumplex model of affect. It discusses recent studies in emotional state influence in various domains and the advancement of sensor technology for real-time emotional state analysis in mobile environments, with a focus on HRV as a measure of emotional arousal. Chapter 3 outlines the goal of developing a complex classification/regression model for emotion detection, integrating multiple physiological signals into a desktop application. It includes research questions aimed at understanding the correlation between HRV and different emotional states, and a detailed methodology involving data collection, processing, stimuli classification, and feature analysis using various techniques like machine learning. Chapter 4 will focus on testing the developed models and applications to ensure the accuracy and effectiveness of emotion detection. Finally, Chapter 5 will provide a comprehensive evaluation of the study, discussing the insights gained in the field of Artificial Emotional Intelligence (AEI), the efficacy of the proposed methods, and suggesting avenues for future research."

CHAPTER 2

Literature Review

This chapter will encompass all the essential background information necessary to grasp the intricacies of the study's subject matter, which focuses on the exploration of emotional arousal through heart rate variability (HRV) in online applications. It will provide a comprehensive overview of the foundational theories and technological advancements in psychophysiology, particularly emphasizing the role of HRV as a critical measure for understanding emotional states.

2.1 Measuring Emotion Arousal for Online Arousal

The exploration of emotional arousal through heart rate variability (HRV) in online applications is a burgeoning area of research in psychophysiology, drawing on foundational theories and technological advancements. Originating from the seminal work in 1995 [63], which emphasized the profound impact of emotions on human behavior and cognitive performance, this field has expanded to incorporate a multidimensional understanding of emotions. The circumplex model of affect plays a pivotal role in this regard, categorizing emotions in terms of valence and arousal, thereby providing a nuanced framework for emotional analysis [64]. A Building on this conceptual foundation, recent studies have ventured into practical applications, examining how emotional states influence various domains such as learning and memory. Pioneering work has been conducted in enhancing mobile working memory training with effective feedback [65]. Concurrently, research has investigated the neurobiological underpinnings of stress and emotional memory processing, highlighting how physiological responses are intricately linked to emotional experiences [66].

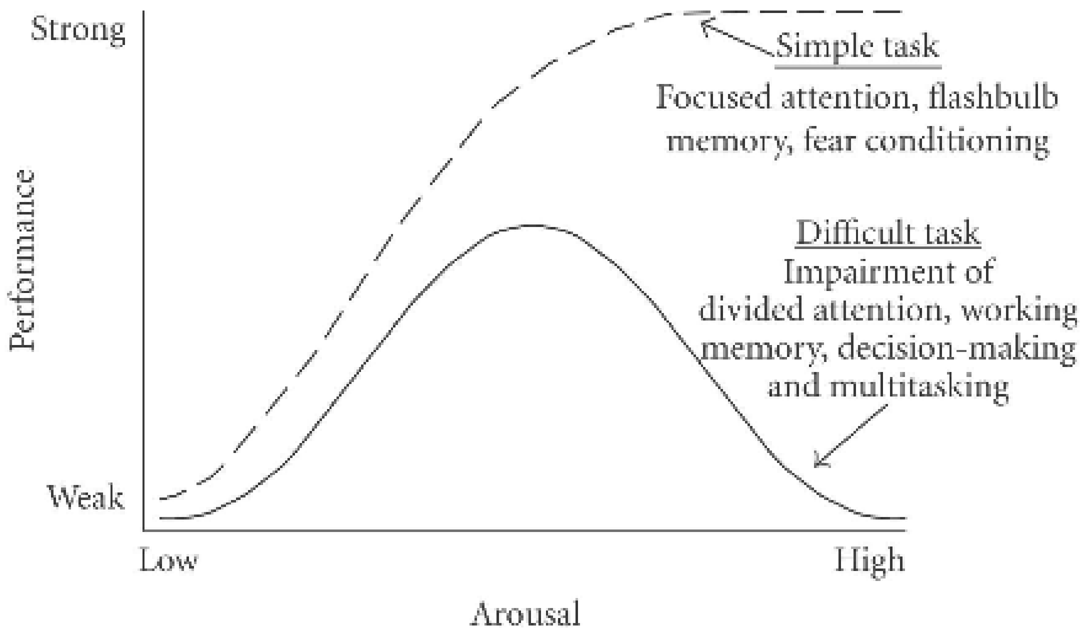

Fig. 1. The Yerkes-Dodson-Law [4]

Figure 2.1: The Yerkes-Dodson Law illustrating the relationship between arousal and performance [2].

The advancement of sensor technology has been instrumental in enabling the non-intrusive collection of physiological data, thereby facilitating real-time emotional state analysis in mobile environments. Significant strides have been made in recognizing emotional states from physiological data. Such breakthroughs have significant implications for developing emotion-aware systems [67],[68], as seen in the application to learning environments [69], [70] and interactive gaming [71], [72].

Focusing specifically on HRV as a measure of emotional arousal, the present study contributes to this evolving landscape by examining the efficacy of ultra-short term HRV measures. Challenging the traditional norms, which typically rely on a 5-minute window for HRV analysis [73], this research investigates the potential of shorter times. By analyzing various HRV features within these condensed windows, the study aims to discern high and low arousal states with accuracy.

The exploration of time and frequency domain features of HRV is particularly

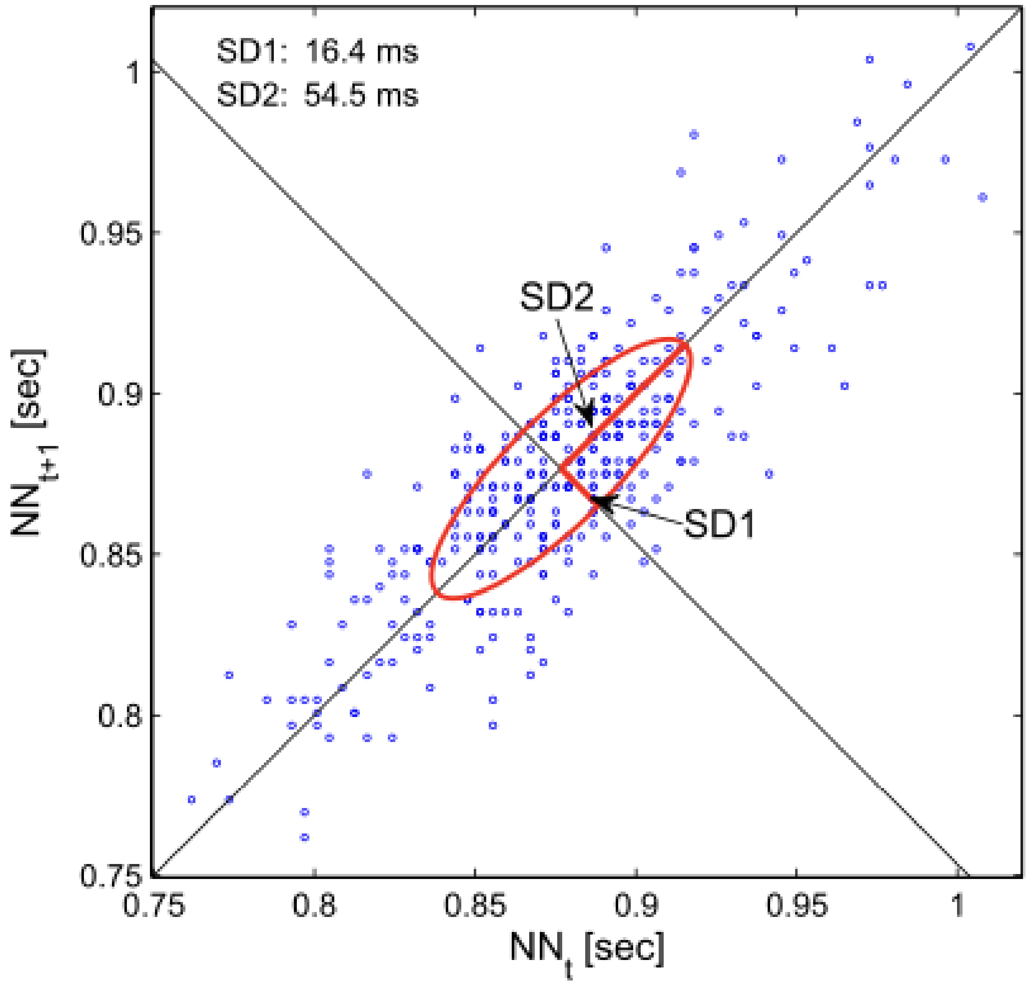

Fig. 2. Poincaré plot for 5 minutes of ECG data during baseline

Figure 2.2: PoincarÃ© plot for 5 minutes of ECG data during baseline [1].

significant in understanding the physiological markers of emotional arousal. This aspect of the research is crucial for developing sophisticated classifiers capable of real-time emotional state recognition in online scenarios. Moreover, the integration of HRV analysis in mobile and wearable technology opens new avenues for personalized feedback systems, catering to individual emotional and cognitive needs.

2.1.1 Methodology

2.1.2 Results

The results of the research paper "Measuring Emotional Arousal for Online Applications: Evaluation of Ultra-Short Term Heart Rate Variability Measures" are pivotal in understanding the effectiveness of HRV analysis in real-time emotional arousal monitoring in online applications. The research investigates the potential of ultra-short term HRV measures in discerning high and low arousal states, challenging the traditional norms of HRV analysis that typically rely on longer time windows.

TABLE II. MEAN VALUES AND STANDARD DEVIATIONS FOR THE RESPECTIVE WINDOW SIZES AND ANOVA RESULTS FOR HA TREATMENT

	Window size				ANOVA results		
	15	30	60	300	F-Value	SE	$HSD_{95\%}$
meanNN	636.361 (124.810)	638.082 (124.265)	640.425 (125.079)	639.639 (121.034)	0.012	22.795	58.987
SDNN	26.805 (16.356)	30.455 (15.765)	34.013 (16.347)	40.218 (16.962)	7.192***	3.013	7.796
RMSSD	21.900 (16.143)	23.034 (15.870)	23.203 (15.093)	24.493 (15.514)	0.271	2.883	7.461
pNN12	0.405 (0.258)	0.417 (0.280)	0.426 (0.270)	0.427 (0.258)	0.077	0.051	0.131
pNN20	0.264 (0.231)	0.271 (0.245)	0.281 (0.240)	0.281 (0.231)	0.068	0.045	0.116
pNN50	0.078 (0.108)	0.077 (0.108)	0.075 (0.111)	0.077 (0.108)	0.006	0.021	0.054
SD1	16.644 (11.980)	17.023 (11.243)	16.846 (10.721)	17.430 (10.956)	0.052	2.069	5.353
SD2	32.380 (20.117)	38.506 (19.912)	44.255 (21.393)	53.606 (22.470)	10.901***	3.866	10.005
SD1/SD2	0.550 (0.301)	0.456 (0.224)	0.390 (0.214)	0.321 (0.116)	10.504***	0.043	0.110
LF	-	0.373 (0.170)	0.326 (0.151)	0.234 (0.115)	13.514***	0.027	0.064
HF	-	0.190 (0.097)	0.156 (0.090)	0.115 (0.073)	10.941***	0.016	0.038
LF/HF	-	3.077 (3.974)	3.601 (5.076)	3.208 (2.893)	0.264	0.751	1.776

* $p < .05$; ** $p < .01$; *** $p < .001$

Figure 2.3: Mean values and standard deaviations [3].

The paper presents a detailed analysis of various HRV features within these condensed windows, emphasizing the reliability and accuracy of these measures in emotional arousal detection. The results indicate that specific HRV features, particularly those analyzed over shorter time windows, can accurately classify emotional arousal, offering significant insights for real-time applications.

This study's findings have profound implications for developing sophisticated emotional recognition systems that can operate in real-time, such as in mobile or online learning environments, interactive gaming, and other dynamic scenarios. The integration of HRV analysis in wearable technology also opens avenues for personalized feedback systems, catering to individual emotional and cognitive needs.

The research contributes significantly to the evolving landscape of biofeedback and psychophysiological studies, highlighting the role of ultra-short term HRV measures in the accurate and real-time monitoring of emotional states. This represents a considerable

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* $p < .05$; ** $p < .01$; *** $p < .001$

Figure 2.4: Fisher's Discriminant ratio for all features

[4].

advancement in the field, demonstrating the potential of HRV in a wide range of applications where understanding and responding to human emotions is crucial.

2.2 A Circumplex Model of Affect

The research paper "A circumplex model of affect" discusses how all affective states arise from cognitive interpretations of core neural sensations, a concept divergent from the theories of basic emotions which posit discrete neural systems for each emotion [56]. This model is more consistent with many recent findings from behavioral cognitive neuroscience, neuroimaging, and developmental studies of affect, and offers new theoretical and empirical approaches to studying affective disorders and their genetic and cognitive underpinnings.

It critiques the traditional experimental paradigm in affective neuroscience research, which categorizes emotions into discrete and independent categories. This basic emotion theory has not fully explained the comorbid illnesses among mood disorders nor resolved confusion over the neurophysiological underpinnings of affective disorders [57].

Dimensional models, like the circumplex model, view affective states as arising from two fundamental neurophysiological systems related to valence and arousal. Each emotion is understood as a combination of these two dimensions [60]. The circumplex model offers a conceptual and experimental framework for exploring the neural basis

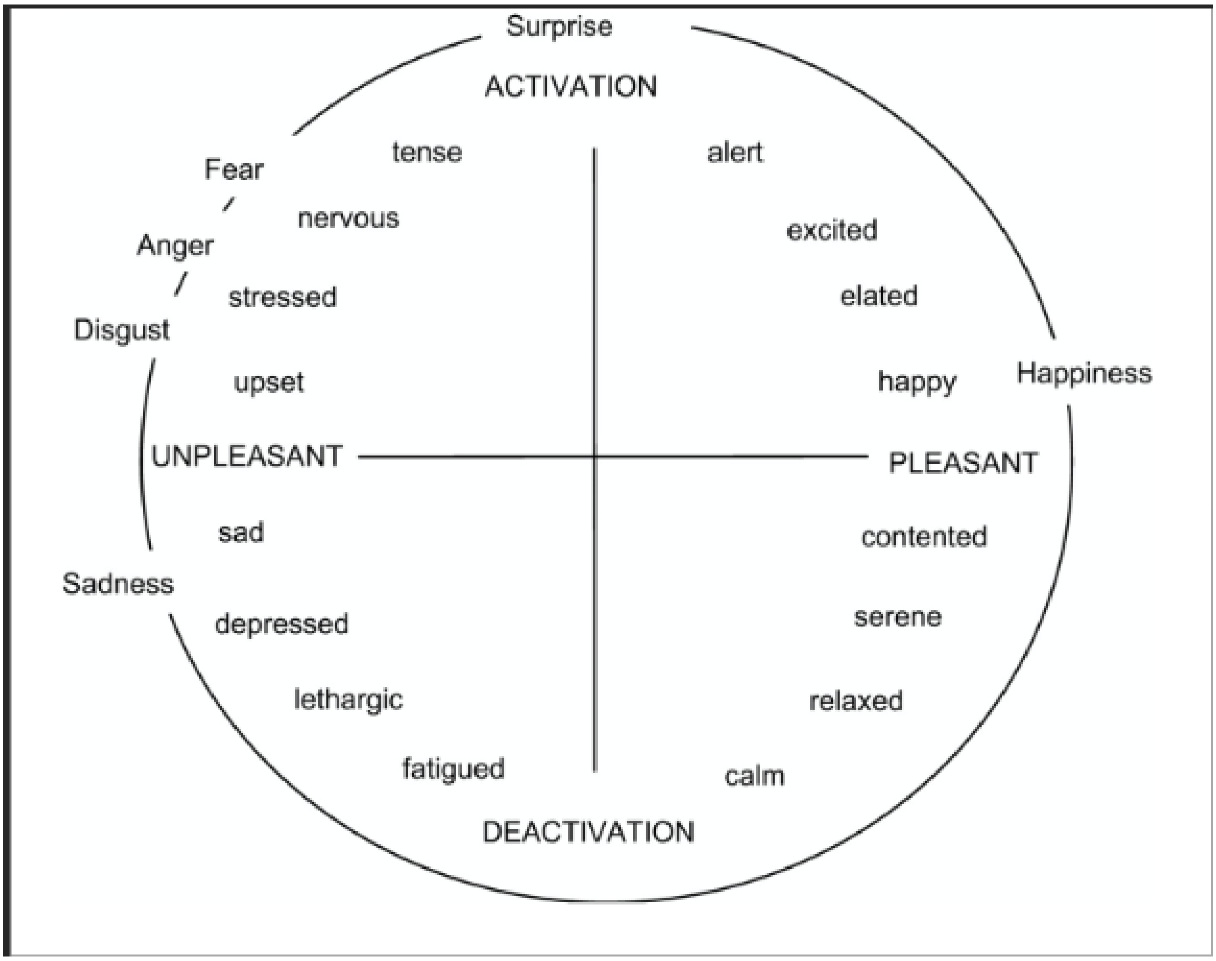


Figure 2.5: Circumplex model of affect

[64]

of affect and provides insight into the neurophysiology of affective disorders [58]. The paper also examines the limitations of basic emotion theories that consider emotions as discrete and independent, primarily derived from affective research with animals. This approach has been limited in providing comprehensive information about affective experiences and the neural systems that support them [59].

2.2.1 Methodology

The paper commences with a thorough examination of the extant theories of emotion, specifically scrutinizing the theory of fundamental emotions. This prepares the audience for the introduction of the circumplex affect model. The authors employ statistical techniques such as multidimensional scaling and factor analysis to examine the relationships between emotional experiences. Examining subjective accounts of emotive words, faces, and experiences allows for this. Biological and Neurophysiological Correlates:

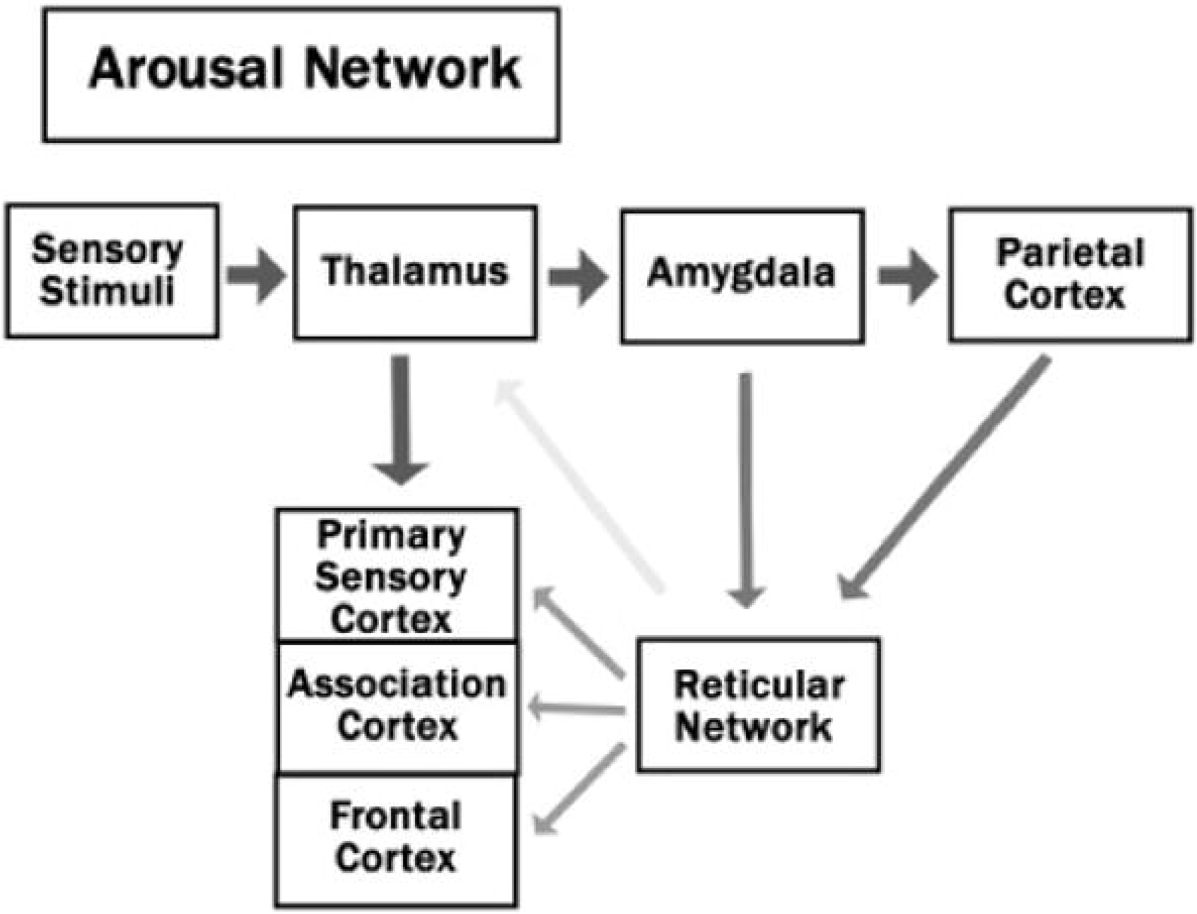


Figure 2.6: The patways of arousal network

[62]

Research on the relationship between brain imaging findings and subjective assessments of valence and arousal is covered in this paper. This includes skin conductance and heart rate acceleration tests, as well as fMRI and EEG studies.

2.2.2 Results

Two Dimensions Emerge: The analysis consistently identifies a two-dimensional structure for affective experience, which has been variously referred to as valence/arousal, tension/energy, or positive/negative affect. Biological Correlates: Subjective assessments of arousal are correlated with increases in skin conductance and heart rate accelerations. Measurements of facial electromyography correlate with valence ratings. Valence-Neural Circuitry: Data are shown regarding the mesolimbic dopamine system's

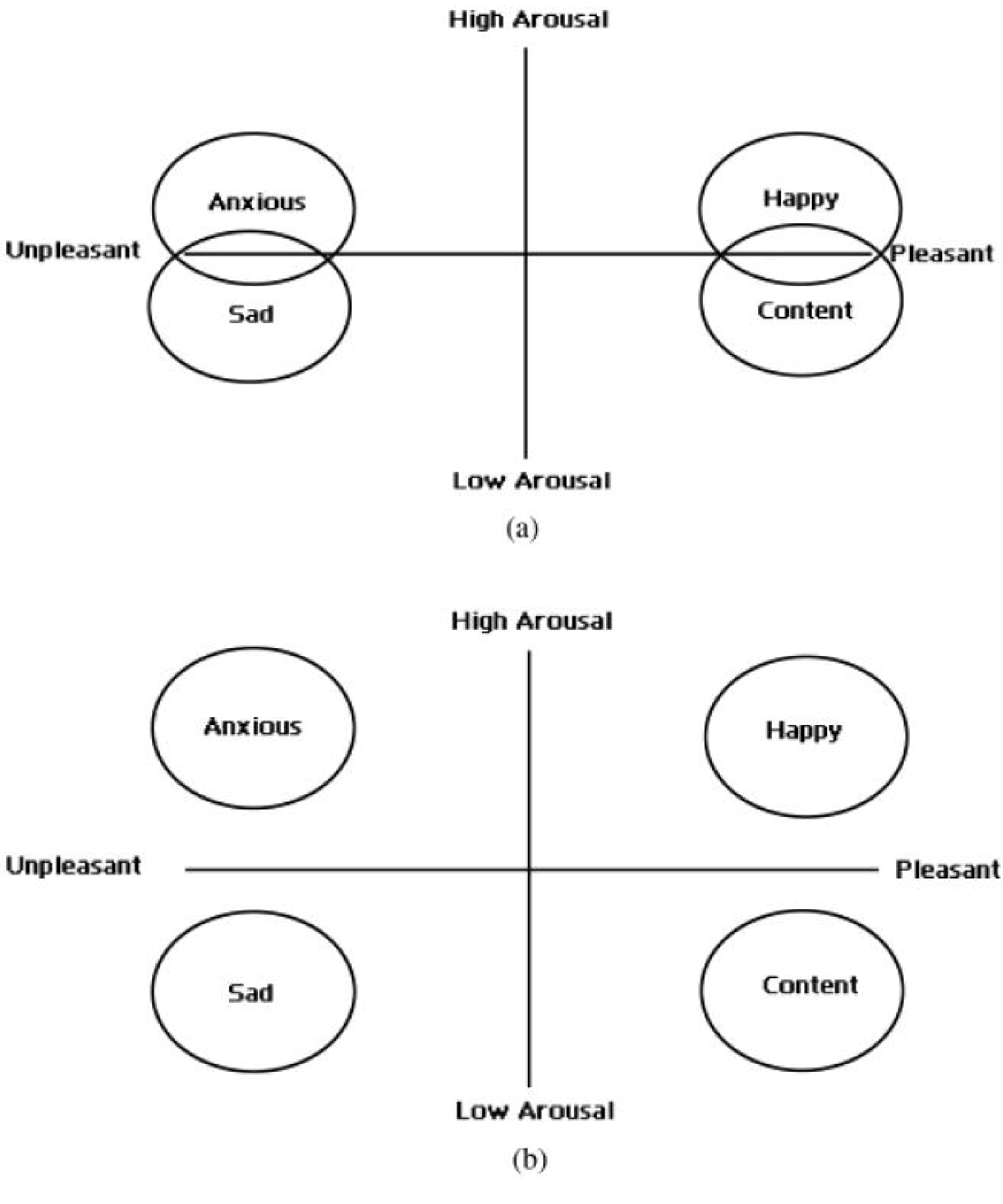


Figure 2.7: (a) The circumplex model with valence focus. (b) The normal circumplex model without valence focus.

[16]

function in reward and pleasure processing, with implications for both happy and sad feelings. Arousal-Neural Circuitry: The central nervous system's ability to regulate arousal levels is attributed to the reticular formation (RF) and its connections.

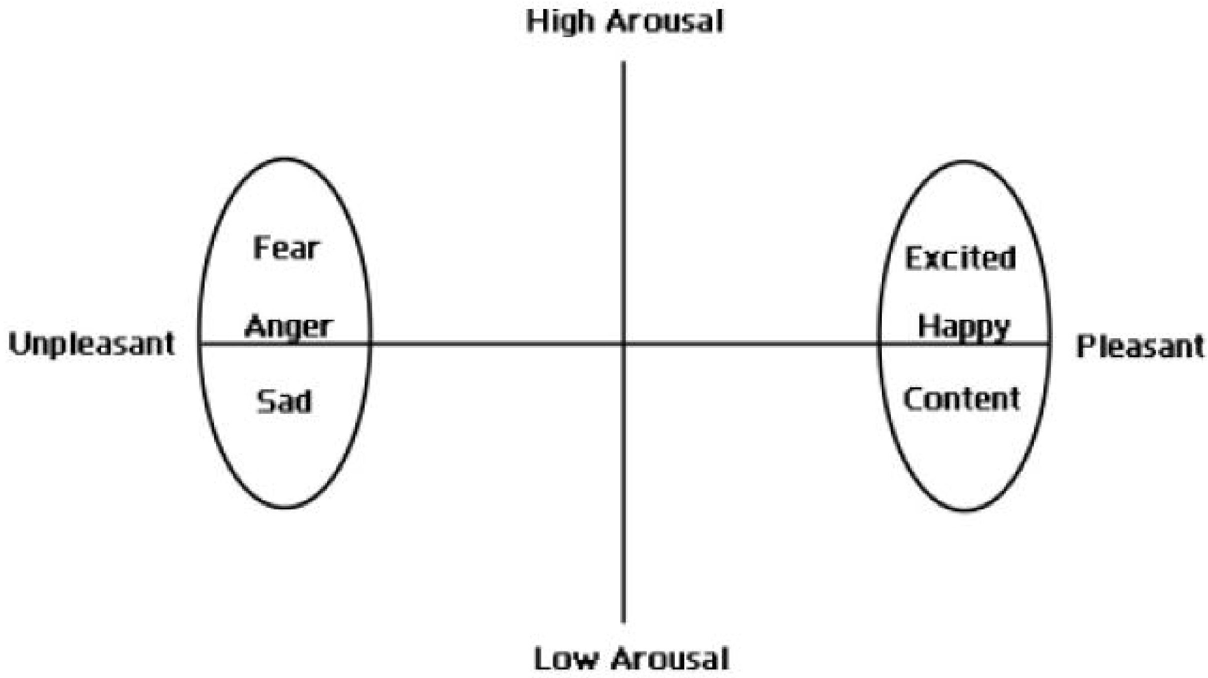


Figure 2.8: The affective circumplex of children.

[13]

2.3 ECG Signal Processing Algorithms to Determine Heart Rate

The research paper "ECG Signal Processing Algorithms to Determine Heart Rate" offers a comprehensive exploration of electrocardiogram (ECG) signal processing, emphasizing the development and implementation of algorithms for accurate heart rate determination. Central to this study is the focus on preprocessing ECG signals to isolate heartbeats and calculate inter-beat intervals, which are crucial for determining heart rate variability (HRV), a key indicator of autonomic nervous system function. The researchers address familiar challenges in ECG signal analysis, such as removing noise and artifacts like baseline wander and power line interference, employing various filtering techniques to ensure signal fidelity [46], [47].

Moreover, the study delves into the significance of HRV as a diagnostic tool, elaborating on its parameters to assess the balance between the sympathetic and parasympathetic nervous systems and their implications for cardiovascular health [48], [49]. In terms of technical implementation, the paper describes the use of Python for algorithmic processing of ECG signals, including the detection and calculation of RR-intervals, a

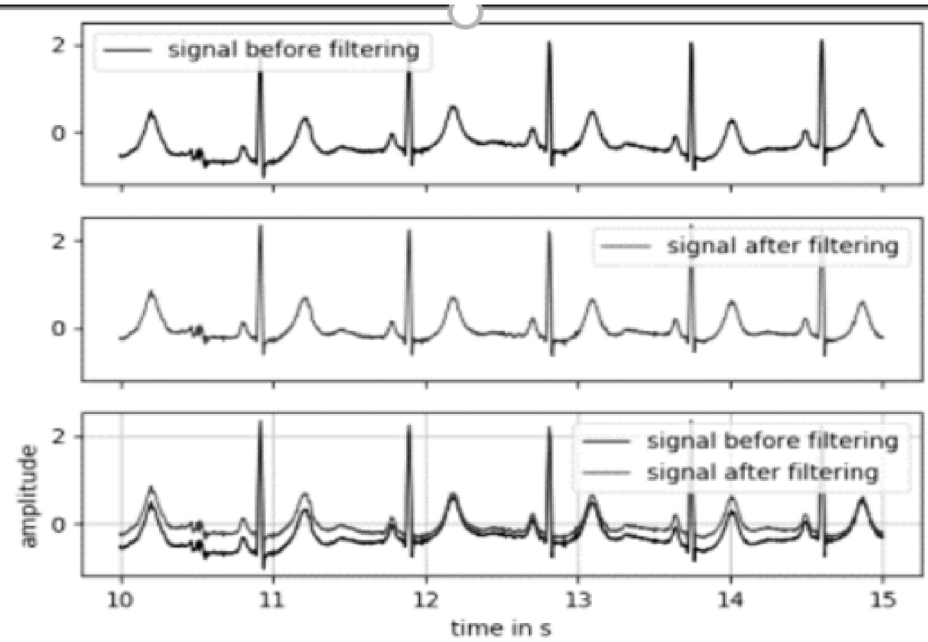


Fig. 1. Elimination of baseline deviation. Comparison of the signal before and after filtering

Figure 2.9: Elimination of baseline deviation.

[5].

fundamental step in heart rate analysis [54], [55]. This approach highlights the potential of these algorithms in clinical diagnostics, where accurate and efficient processing of ECG data can significantly improve the assessment of cardiovascular conditions [50], [51].

Furthermore, the paper points to the future of this field, suggesting the integration of these algorithms into real-time monitoring systems and personalized healthcare applications. This direction underscores the evolving role of digital signal analysis in healthcare, transitioning from traditional methods to more sophisticated, automated approaches [52] [53].

2.3.1 Methodology

In the paper, heart rate is calculated by processing ECG signals. It consists of initial ECG signal processing, frequency filtering, feature extraction, and feature calculation for heart rate estimation. The study uses software and algorithmic implementation in Python for R-peak detection and signal processing. Along with calculating RR-intervals, the methodology investigates the application of different heart rate variability (HRV) parameters.

2.3.2 Results

The paper uses ECG signal processing to calculate heart rate. It comprises feature extraction, feature calculation for heart rate estimation, frequency filtering, and initial ECG signal processing. Software and algorithmic Python implementation are used in the study to process signals and detect R-peak. The methodology not only computes RR-intervals but also explores the use of various heart rate variability (HRV) parameters.

2.4 Early and later Post-Exercise Heart Rate Variability Analysis of ECG Signals

2.4.1 Introduction and Background

The paper starts by introducing the ECG as a heart-generated electrical signal, important for various biomedical applications like heart rate measurement, rhythm monitoring, and emotion recognition [6]. The ECG captures the bio-electrical activity of the heart during its cardiac cycle [7],[8].

The introduction also emphasizes the non-invasive nature of ECG for monitoring heart rate and rhythm, which can be affected by physical conditions and exercise [9],[10],[11].

2.4.2 Methodology

Five volunteers participated in the study, and the Biopac MP 45 biomedical signal acquisition device was used to collect the ECG data [12]. The method of preprocessing ECG signals is described in the paper. It involves the removal of baseline wander using wavelet-based techniques [20] and power line interference using notch filter design based on Fast Fourier Transform (FFT) techniques [19].

A straightforward nearest neighbor-based algorithm was employed for R-peak detection, and Kubios HRV Standard 3.1 software was used to validate the HRV analysis, which was carried out in MATLAB [18],[21].

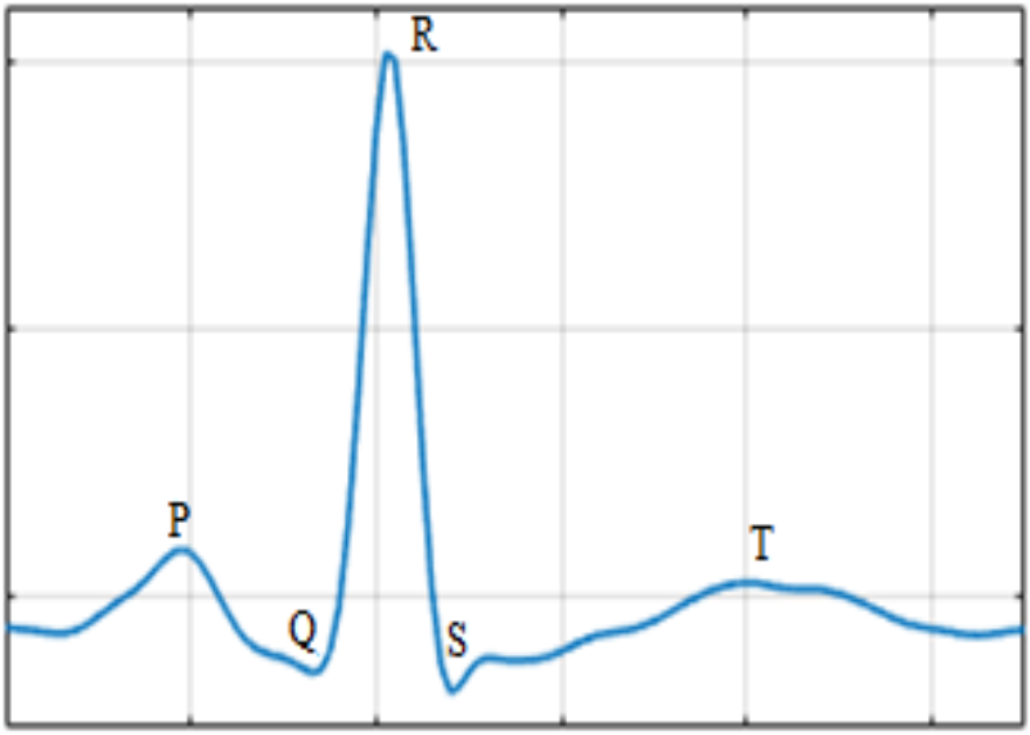


Fig. 1. Single ECG Beat

Figure 2.10: Single ECG Beat.
[22].

2.4.3 Results

Each participant's HRV analysis is shown in the results section, along with differences in HRV parameters between the early and later (relaxed) post-exercise conditions.

The time-domain analysis of HRV is covered in the paper, with particular attention paid to parameters such as mean RR interval, SDNN, RMSSD, NN50, and pNN50, all of which demonstrated notable changes in the post-exercise period [18], [21]. In order to show changes in HRV complexity after exercise, non-linear analysis of HRV was also carried out. This included Poincare plots and complexity analysis using approximate entropy, sample entropy, and detrended fluctuation analysis.

2.4.4 Conclusion

The study comes to the conclusion that HRV parameters are useful in both time-domain and frequency-domain analysis, and that they offer important insights into cardiac responses. The study supports the use of HRV as a tool for patient-specific heart disease

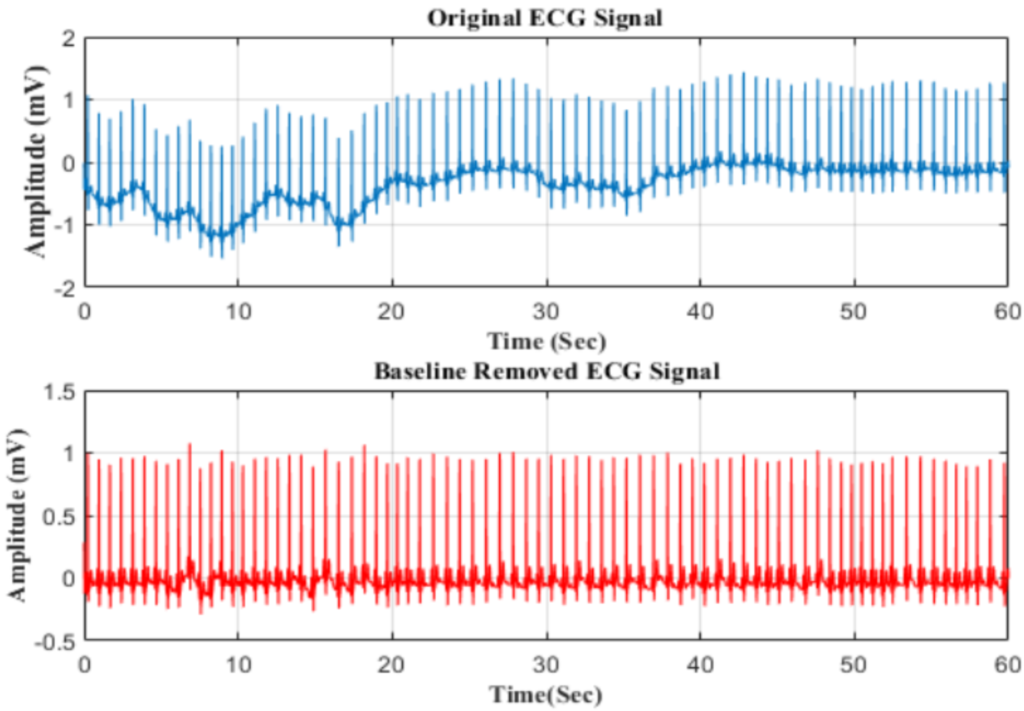


Fig. 6. Plot of Original ECG Signal and Filtered ECG Signal

Figure 2.11: Plot of Orginal ECG Signal and Filtered Signal.

[23].

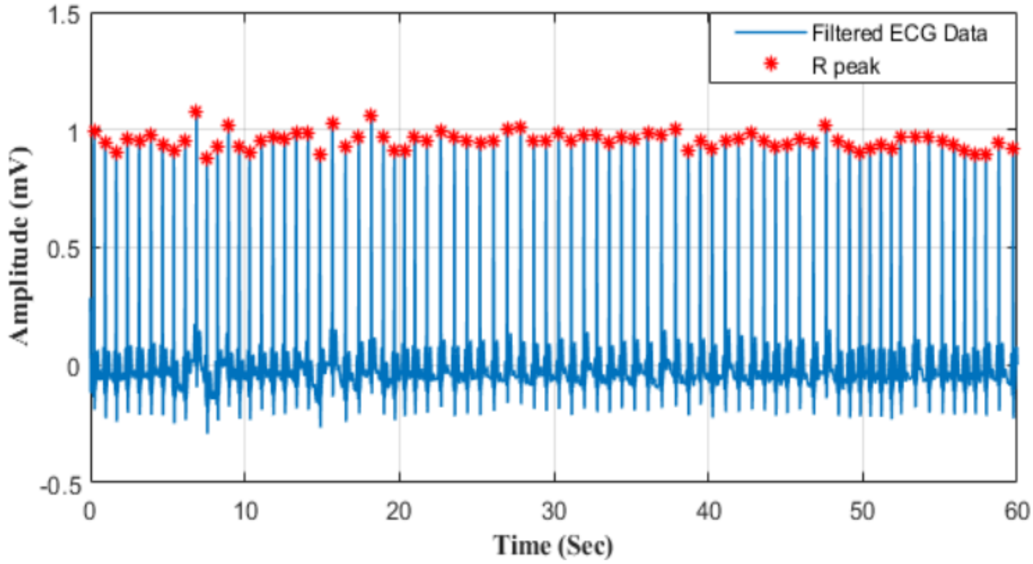
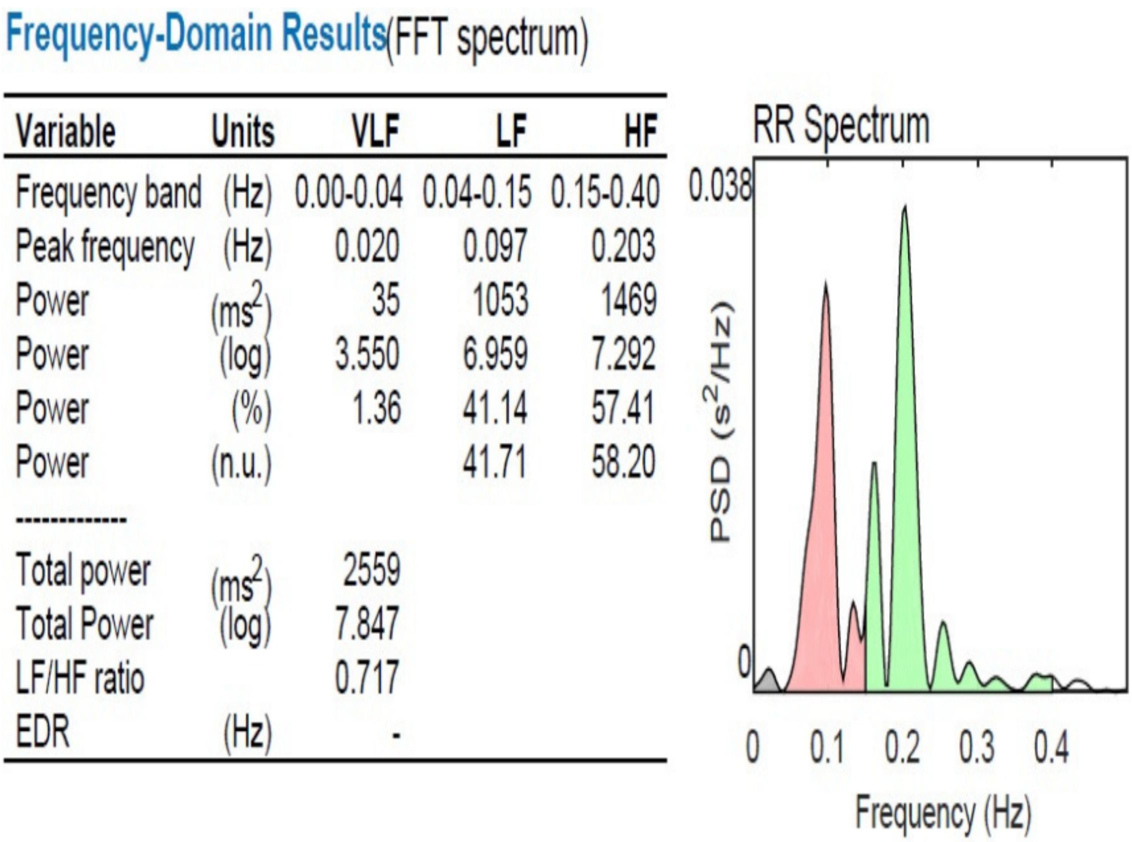


Fig. 7. R-peak Detection (1 min)

Figure 2.12: R-peak Detection.

[24].

monitoring and athlete health monitoring.


Frequency-Domain Results(FFT spectrum)

Variable	Units	VLF	LF	HF
Frequency band	(Hz)	0.00-0.04	0.04-0.15	0.15-0.40
Peak frequency	(Hz)	0.020	0.097	0.203
Power	(ms^2)	35	1053	1469
Power	(log)	3.550	6.959	7.292
Power	(%)	1.36	41.14	57.41
Power	(n.u.)		41.71	58.20

Total power	(ms^2)	2559		
Total Power	(log)	7.847		
LF/HF ratio		0.717		
EDR	(Hz)	-		

Fig. 12. FFT spectrum of Participant I in Later Post Exercise Period (Kubios HRV Standard 3.1 software)

Figure 2.13: FFT spectrum of Participant.

[25].

2.5 Determining Levels of Arousal using Electrocardiography: A study of HRV during Transcranial Magnetic Stimulation

The research study "Determining Levels of Arousal using Electrocardiography: A study of HRV during Transcranial Magnetic Stimulation" employed an extensive and meticulous methodology to explore the use of heart rate variability (HRV) for assessing arousal levels during Transcranial Magnetic Stimulation (TMS) [26], [27], [28]. The study rigorously adhered to ethical standards, commencing with obtaining written and

informed consent from all participants, and receiving approval from the Research Ethics Board of UOIT [29], [30].

2.5.1 HRV and TMS: A Methodological Insight

The research study "Determining Levels of Arousal using Electrocardiography: A study of HRV during Transcranial Magnetic Stimulation" employed an extensive and meticulous methodology to explore the use of heart rate variability (HRV) for assessing arousal levels during Transcranial Magnetic Stimulation (TMS)[26], [27], [28]. The study rigorously adhered to ethical standards, commencing with obtaining written and informed consent from all participants, and receiving approval from the Research Ethics Board of UOIT [29], [30].

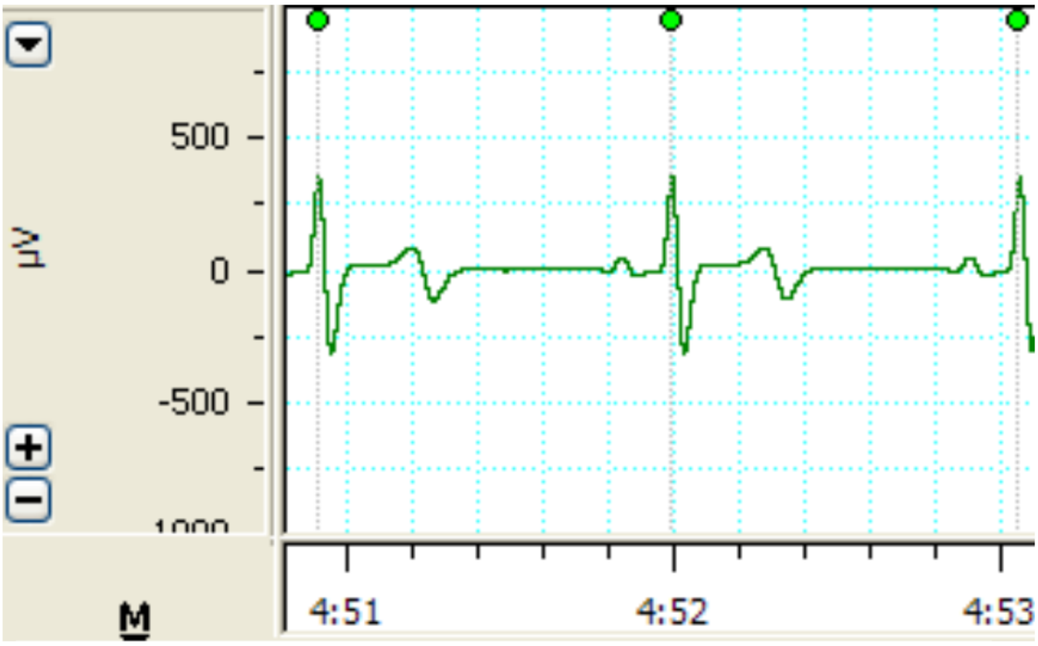


Fig. 1. A view of heart rate data from LabChart™. The round dots indicate R peaks, and the space between is considered the R-R interval.

Figure 2.14: A view of heart rate from Lab Chart.
[44].

The core of the study's data collection involved the strategic use of surface electrodes to monitor heart rate, a crucial parameter in HRV analysis [31], [32]. This data collection was strategically timed to occur at three pivotal stages of each TMS experiment: initially to establish a baseline, midway through the experiment, and at its conclusion [?], [34].

This tri-phasic approach allowed for a comprehensive understanding of heart rate dynamics in response to TMS [35].

In terms of electrode placement, the study adopted a nuanced approach to ensure accuracy and minimize artifacts that could arise from participant movement. One electrode was strategically positioned on the sternum, while the other two were placed with precision mid-axilla on the 5th intercostal space on both the left and right sides of the chest [36], [37]. This specific 3-lead chest placement strategy was informed by previous findings that noted significant movement artifacts when using the more traditional limb leads [41].

Preparing for the actual recording involved detailed procedures to ensure the integrity of the data. Subjects were instructed to sit in a comfortable yet restricted posture to minimize movement during the data collection period [38], [39]. Moreover, the skin where the electrodes were to be placed underwent a careful preparatory process, involving light abrasion followed by cleaning with an alcohol wipe [40]. This meticulous skin preparation was crucial for reducing electrical noise and ensuring high-quality ECG signal acquisition.

The subsequent stage of data processing was a critical part of the study. Using the sophisticated capabilities of LabChart software, researchers collected Electrocardiography (ECG) data and generated the vital R-R intervals, a cornerstone of HRV analysis [42], [43]. This stage involved a detailed examination and determination of the amplitude of each R peak, a procedure that required precision and attention to detail.

The final and perhaps most complex part of the study involved a comprehensive analysis of the HRV. The researchers utilized the exported R-R intervals for a deeper, more insightful analysis, incorporating advanced calculations such as RRV3 and RRV8-3. These calculations are integral to HRV analysis, offering a detailed and sophisticated understanding of heart rate dynamics and variability. This analysis was pivotal in understanding the nuances of HRV as a reliable measure of arousal levels during TMS, providing insights that could have significant implications in both clinical and research settings.

2.5.2 HRV Analysis in TMS: Unveiling Arousal Variability

The study, focused on using heart rate variability (HRV) for assessing arousal levels during Transcranial Magnetic Stimulation (TMS), showed that of the six subjects, five demonstrated periods of decreased arousal throughout the experiment. This was evident through the analysis of R-R intervals using LabChart software, and further determination of RRV3 and RRV8-3 values, where low arousal levels were detected in five of the six analyses [34]. This suggests that HRV effectively measures changes in arousal levels [29], [31]. However, one subject displayed consistently high arousal levels, with RRV8-3 values significantly exceeding RRV3, pointing to individual variability in response to TMS. This observation was particularly intriguing and highlighted the complexity of HRV as a measure of arousal during TMS [35], [37].

The study's findings reinforce the utility of HRV in monitoring arousal levels, with implications for future research involving continuous heart rate collection during TMS to understand the correlation between low arousal states and TMS data changes [27] [28] [30]. The detailed HRV analysis, especially the use of RRV3 and RRV8-3 calculations, provides a nuanced understanding of autonomic nervous system dynamics during TMS sessions. Such insights could have significant applications in both clinical and research settings, emphasizing the importance of continuous monitoring and individualized assessments in TMS experiments [32] [33] [42] [43].

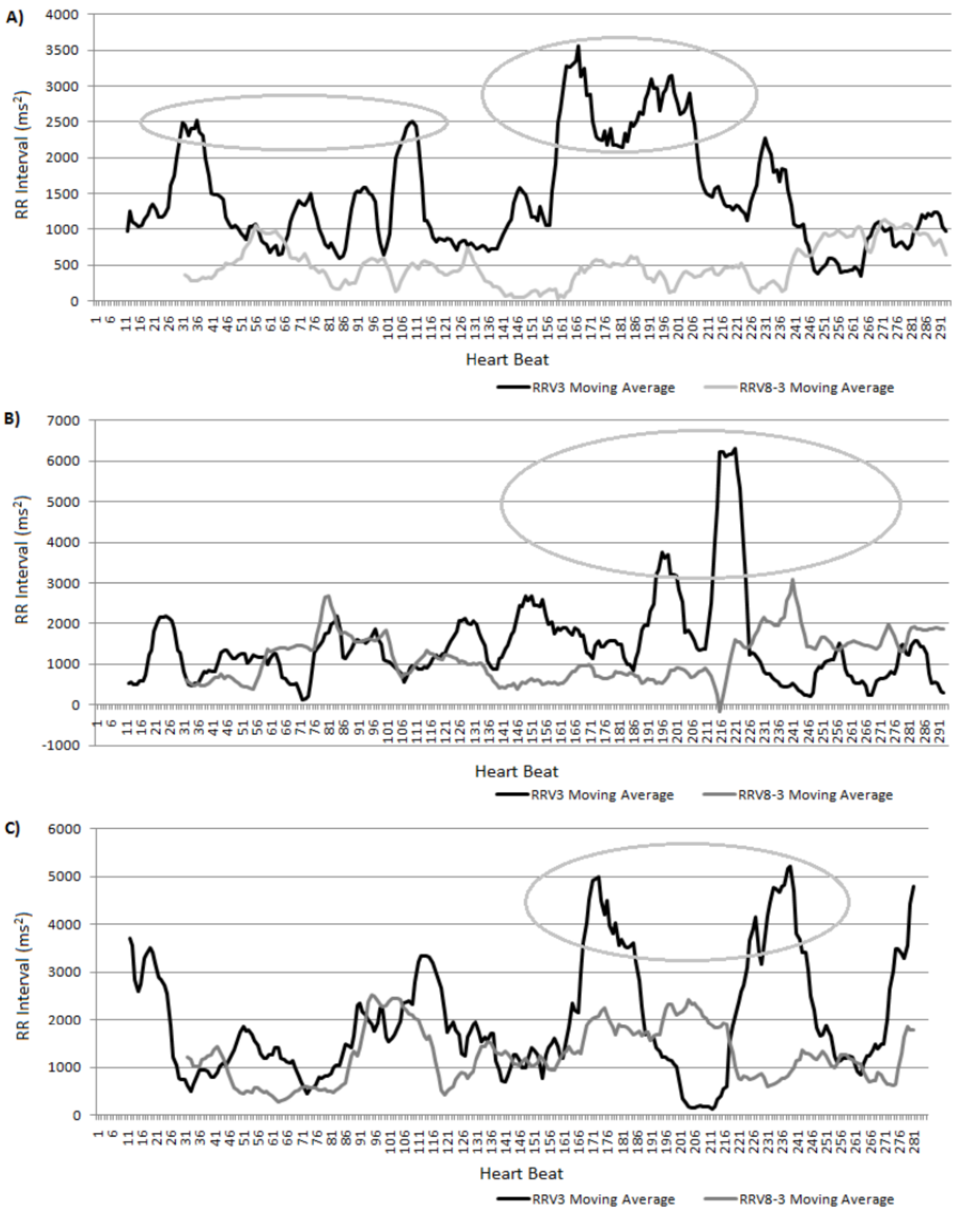


Figure 2.15: A comparison of moving averages of RRV3 (parasympathetic) and RRV8-3 (sympathetic) at baseline (A), halfway through (B), and at the end (C) of the TMS experiment. The circled areas represent periods of low arousal due to increased RRV3. [45].

CHAPTER 3

Project Plan

The project's goal is to create a sophisticated emotion detection model through a thorough methodology that includes iMotions technology's analysis of heart rate data. A variety of physiological signals will be used by this model, such as the electroencephalogram (EEG), facial expressions, galvanic skin response (GSR), and heart rate variability (HRV) from iMotions. The model's design is fundamentally based on the integration of HRV, particularly as processed by iMotions' advanced analytical tools, which provide a deeper understanding of the autonomic nervous system's reactions to emotional stimuli. The goal of the project is to create an intuitive desktop application that can handle and examine.csv files with these kinds of varied data sets. This application will push the limits of current knowledge and application of emotion recognition technologies, in addition to being a useful tool for real-time emotion detection and contributing to the emerging field of Artificial Emotional Intelligence (AEI).

3.1 Objective

The main objective of my study is to analyse physiological signals, particularly heart rate variability (HRV), to explore emotional arousal and stress levels. This involves using machine learning techniques to process and interpret data from various physiological sensors.

3.2 Methodology

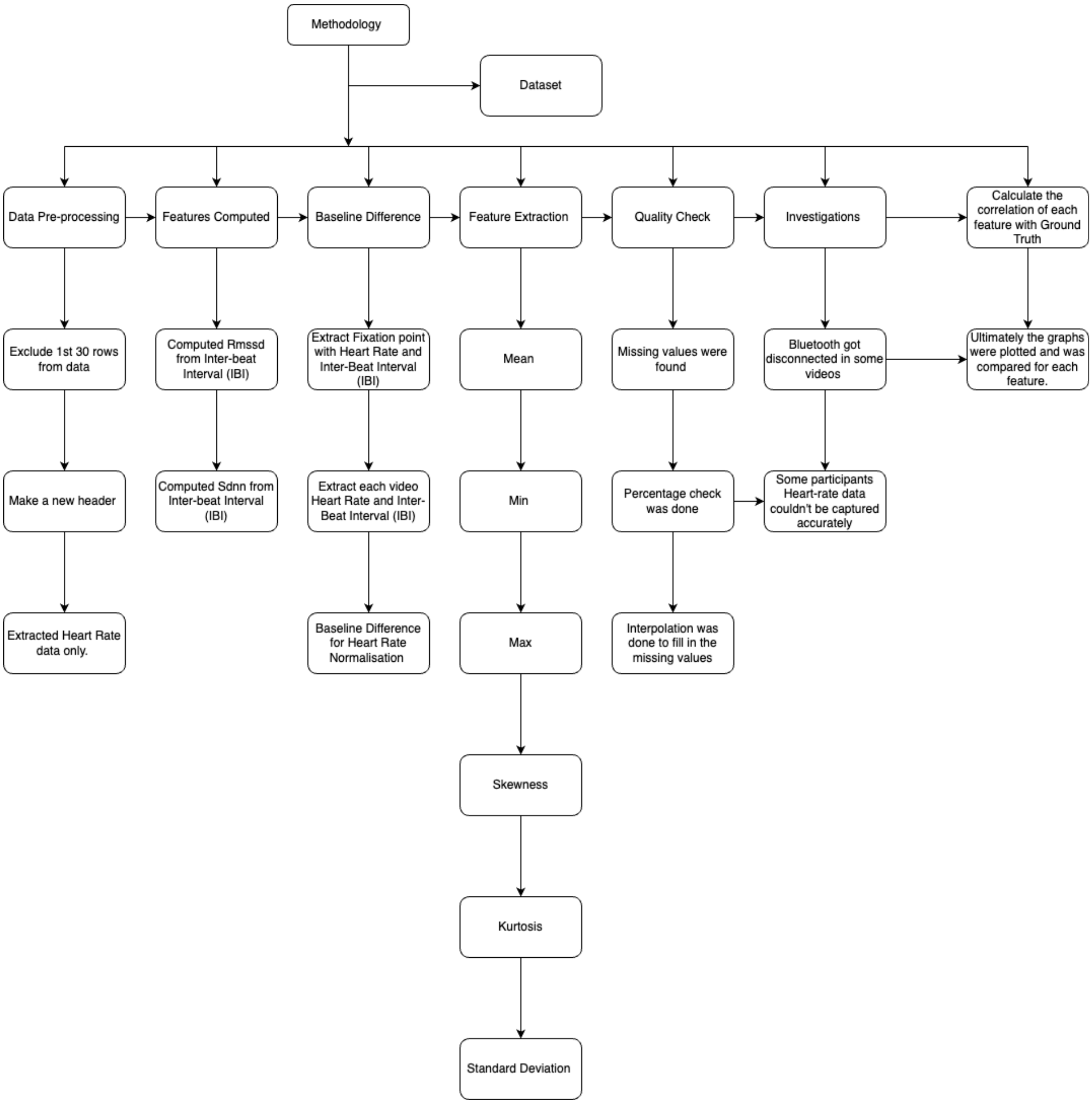


Figure 3.1: A flow chart showing the entire process.

3.2.1 Data Collection

Utilize iMotions software to gather physiological data, including heart rate (HR), HRV, galvanic skin response (GSR), pupil size, and electroencephalogram (EEG) data. Ensure data collection occurs under controlled conditions, where participants are exposed to various stimuli designed to extract emotional responses.

3.2.2 Data Pre-processing

Used the python script (DataAnalyzer) to process the heart rate data, focusing on periods when participants are fixated on a specific point, to establish a baseline on heart rate and HRV. Used another python script to compute RMSSD (Root Mean Square of the Successive Differences) and SDNN (Standard Deviation of NN Intervals) for different stimuli, comparing them against the baseline. Methodology includes a Python script to interpolate heart rate data, essential for addressing gaps or inconsistencies in physiological data. Use linear interpolation methods to ensure continuous, coherent data sets for accurate analysis.

3.2.3 Stimuli Classification

Categorize stimuli into emotional categories based on the circumplex model of affect. Use video emotion mappings for stimuli categorization and response recording.

3.2.4 Feature Extraction and Analysis

The core of your methodology involves extracting key features from the physiological data. You calculate RMSSD and SDNN from HRV data to quantify autonomic nervous system activity. Additionally, you process other physiological signals to extract relevant features, which could include statistical measures like skewness and kurtosis from heart rate data.

3.2.5 Statistical Analysis

Conduct a statistical analysis to understand the relationship between the extracted features and emotional arousal. This includes calculating correlation coefficients and R-squared values to assess the strength of the relationship between physiological signals and emotional states.

3.2.6 The study is structured into three main components

Heart rate variability analysis

Objective:

Compute RMSSD and SDNN for various emotional stimuli.

Data Processing: -

Load data from a CSV file, filter for relevant columns, and map stimuli to emotion labels using a predefined dictionary.

Method: -

Identify Inter-Beat Intervals (IBIs) and find peaks using scipy.signal. Calculate RMSSD and SDNN for these intervals. Aggregate results by emotion into a DataFrame.

Fixation point analysis

Objective: -

Analyze differences in heart rate metrics (RMSSD, SDNN) during fixation points compared to various stimuli.

Data Processing: -

Use the DataAnalyzer class for data management, including loading and preprocessing.

Method:-

Compute RMSSD and SDNN for fixation points. Calculate differences in these metrics compared to other stimuli. Present differences in a structured DataFrame format.

Statistical feature analysis

Objective: -

Investigate the relationship between emotional arousal and statistical features (mean, max, min, skewness, kurtosis, standard deviation differences).

Data Processing:-

Load and clean data from a CSV file. Prepare the dataset by normalizing column names and handling missing values.

Method: -

Calculate correlations between emotional arousal and each statistical feature. Perform linear regression analysis and visualize these relationships using scatter plots with regression lines. Compute and display correlation coefficients and R-squared values for each feature, elucidating the strength and nature of these relationships.

Correlation Analysis: -

As part of examining relationships between emotional arousal and statistical features, include a correlation analysis.

Utilize Python libraries to calculate correlation coefficients between arousal levels and various physiological features.

Correlation analysis helps in identifying which physiological signals are most strongly associated with specific emotional states.

3.2.7 Expected Outcomes

Develop a model predicting emotional states from physiological data. Create a desktop application for real-time emotion detection.

Gain insights into the correlation between physiological signals and emotional states, enhancing AEI research.

3.3 Research Questions

How does heart rate variability (HRV) correlate with different emotional states?

This question delves into the physiological aspects of emotional processing. HRV, a measure of the variation in time between consecutive heartbeats, is influenced by the autonomic nervous system. It is known to vary with different psychological states. Research under this question would investigate how specific patterns of HRV correspond to distinct emotions like happiness, sadness, stress, or relaxation. It would involve measuring HRV responses in various emotional scenarios and analyzing the data to identify patterns that reliably indicate emotional states.

How does the integration of heart rate data with other psychological measures in emotions enhance the understanding of complex emotional states?

Emotional states are multi-dimensional and can be influenced by various physiological and psychological factors. This question explores the benefits of a comprehensive approach to emotion analysis by combining heart rate data with other measures like facial expressions, galvanic skin response, or EEG. The integration aims to provide a more comprehensive understanding of complex emotional states that may not be fully captured by heart rate data alone. Research here would involve cross-referencing

HRV data with other psychological indicators to see how they collectively contribute to identifying and understanding complex emotions.

Can imotions effectively differentiate between various stress levels using heart rate variability and other physiological measures?

iMotions is a software platform that integrates and analyzes data from multiple sensors. This question is about its efficacy in using HRV, along with other physiological data, to differentiate between varying levels of stress. The research would involve setting up experiments to induce different stress levels and then using iMotions to analyze HRV and other physiological measures (like skin conductance or facial expressions) to see if it can accurately distinguish between these stress levels. This could have implications for stress management, therapy, and understanding how people react to different stressors.

What is the effectiveness of imotions in real time heart rate monitoring for biofeedback applications?

This question assesses the capability of iMotions in providing real-time feedback based on heart rate monitoring. Biofeedback is a process where individuals are provided with information about their physiological processes (like heart rate) in real time, enabling them to learn to control these functions. The research would test how effectively iMotions can monitor heart rate in real-time and how this data can be used in biofeedback applications. This has significant implications for therapeutic techniques, especially in treating conditions like anxiety or stress, where biofeedback can be a crucial tool.

CHAPTER 4

Results

4.1 Rmssd and Sdnn

From the table below, we observe a range of values for both RMSSD and SDNN across different videos. The variations in these values could be attributed to the participant's different physiological responses to the emotional or physical stimuli presented in each video. Typically, the context of the videos would provide further insight into the autonomic responses. For example, a stressful video might result in lower RMSSD and higher SDNN, indicating increased heart rate variability due to stress.

The highest RMSSD value is seen with video M, which might imply that the content of this video induced a state of relaxation or positive emotions, enhancing parasympathetic activity. On the other hand, the lowest RMSSD value corresponds to video W, which could suggest less parasympathetic activation during this stimulus.

For SDNN, the highest value is found in video F, and the lowest in video W. Since SDNN encompasses overall heart rate variability, the high value in video F might indicate a greater capacity for physiological resilience or a response to a dynamic stimulus.

These results can be used to analyze the relationship between the participant's emotional response to various stimuli and their autonomic nervous system activity. However, to draw more specific conclusions, we'd need to know the nature of the stimuli in each video and consider additional contextual factors and individual baseline

articipant Name	Video	RMSSD	SDNN
Group33_v5_3	A1	29.841033	16.834076
Group33_v5_3	A2	26.641165	16.697861
Group33_v5_3	A3	25.839652	14.957925
Group33_v5_3	A4	25.175914	14.425859
Group33_v5_3	A	24.705294	12.860998
Group33_v5_3	B	29.538539	16.229703
Group33_v5_3	C	30.185554	17.713217
Group33_v5_3	F	32.635310	20.503162
Group33_v5_3	G	25.212832	13.606109
Group33_v5_3	H	33.025319	19.250852
Group33_v5_3	J	26.337958	15.235145
Group33_v5_3	K	21.844540	12.387761
Group33_v5_3	M	33.558860	22.720620
Group33_v5_3	N	25.874866	16.619602
Group33_v5_3	O	29.769091	17.409366
Group33_v5_3	P	29.231698	18.708246
Group33_v5_3	Q	28.858873	18.159157
Group33_v5_3	U	31.347504	18.912060
Group33_v5_3	V	30.183793	16.685807
Group33_v5_3	W	18.900666	10.634592

Figure 4.1: Values that were computed for Rmssd and Sdnn

variability.

4.2 Baseline

Positive values indicate an increase in HRV metrics compared to the baseline, suggesting a relaxed or less stressed state during that video stimulus.

Negative values (as seen in the rows for videos H and M) indicate a decrease in HRV metrics compared to the baseline, which might suggest increased stress or attention

participant name	video name	RMSSD difference	SDNN difference
group33_v5_10	A1	2.584047	1.738369
group33_v5_10	A2	4.785687	3.810791
group33_v5_10	A3	7.367989	3.996742
group33_v5_10	A4	3.822061	2.071555
group33_v5_10	A	6.982176	3.356780
group33_v5_10	B	0.048119	-0.048817
group33_v5_10	C	1.613893	0.714150
group33_v5_10	F	0.157780	0.218687
group33_v5_10	G	0.149691	0.148005
group33_v5_10	H	-0.003262	0.272603
group33_v5_10	J	2.301071	1.297606
group33_v5_10	K	3.401120	3.755130
group33_v5_10	M	0.026298	-0.269852
group33_v5_10	N	3.368561	1.388886
group33_v5_10	O	2.036979	2.026486
group33_v5_10	P	0.089443	0.314423
group33_v5_10	Q	4.618903	2.059091

Figure 4.2: The differences that were computed from the video stimuli and from the fixation point

demand during that video stimulus.

Larger positive numbers reflect a more significant increase from the baseline. For example, the values for videos A2 and A3 are quite high, which could mean these videos were particularly calming or required less cognitive effort from the participant.

The relatively small or negative differences suggest that there was little change or a decrease in HRV metrics from the baseline, which could be interpreted as a possible increase in stress or cognitive demand.

4.3 Testing

Unless otherwise noted, all of the tests listed in the testing chapter were performed using the system specifications listed below:

Processor

Apple M1 Chip, 8-Core CPU (4 Performance Cores, 4 Efficiency Cores), Integrated 8-Core GPU.

Memory

8GB

Graphics

Apple M1 Integrated 8-Core GPU.

Storage

Apple MacBook Air (M1) with 256GB SSD Storage.

OS

macOS

The following platforms were used for testing purposes: -

Google Colab

Pycharm

VSCode

Most of the test were conducted on google colab, and the codes were made dynamic to take the data from the google drive as all the datasets were uploaded on the google drive and even the output was automatically saved on the google drive after the values were computed.

4.4 Graphs before interpolation

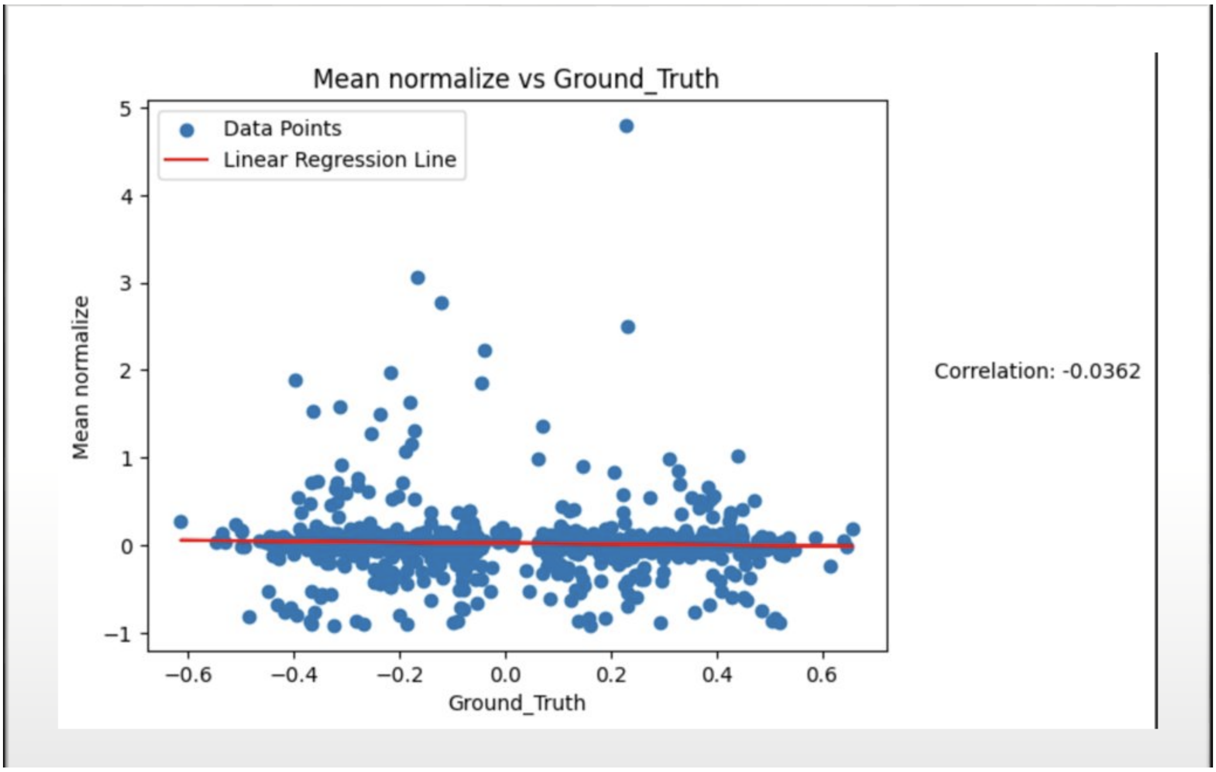


Figure 4.3: Feature - Mean

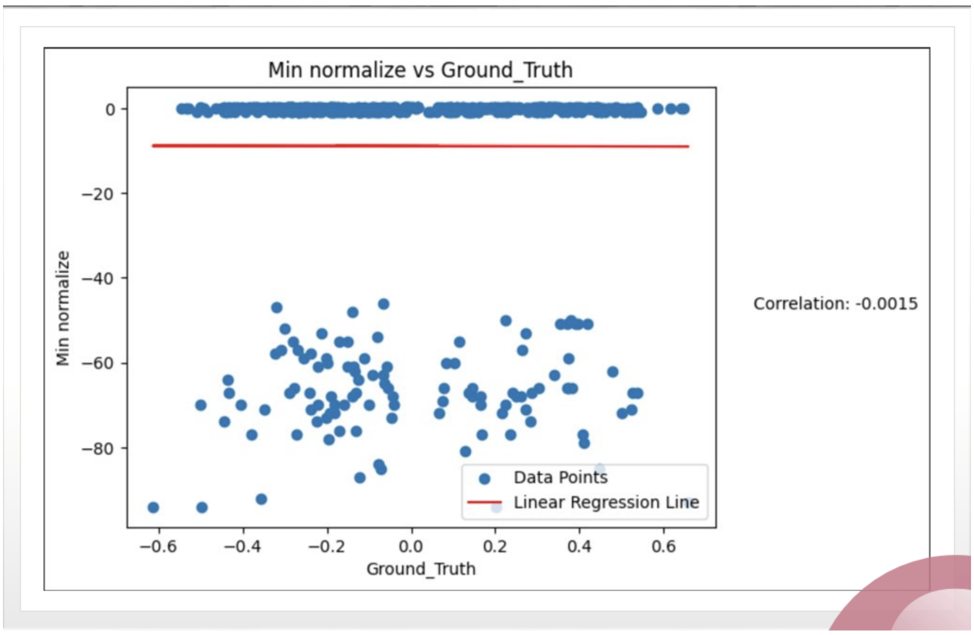


Figure 4.4: Feature - Min

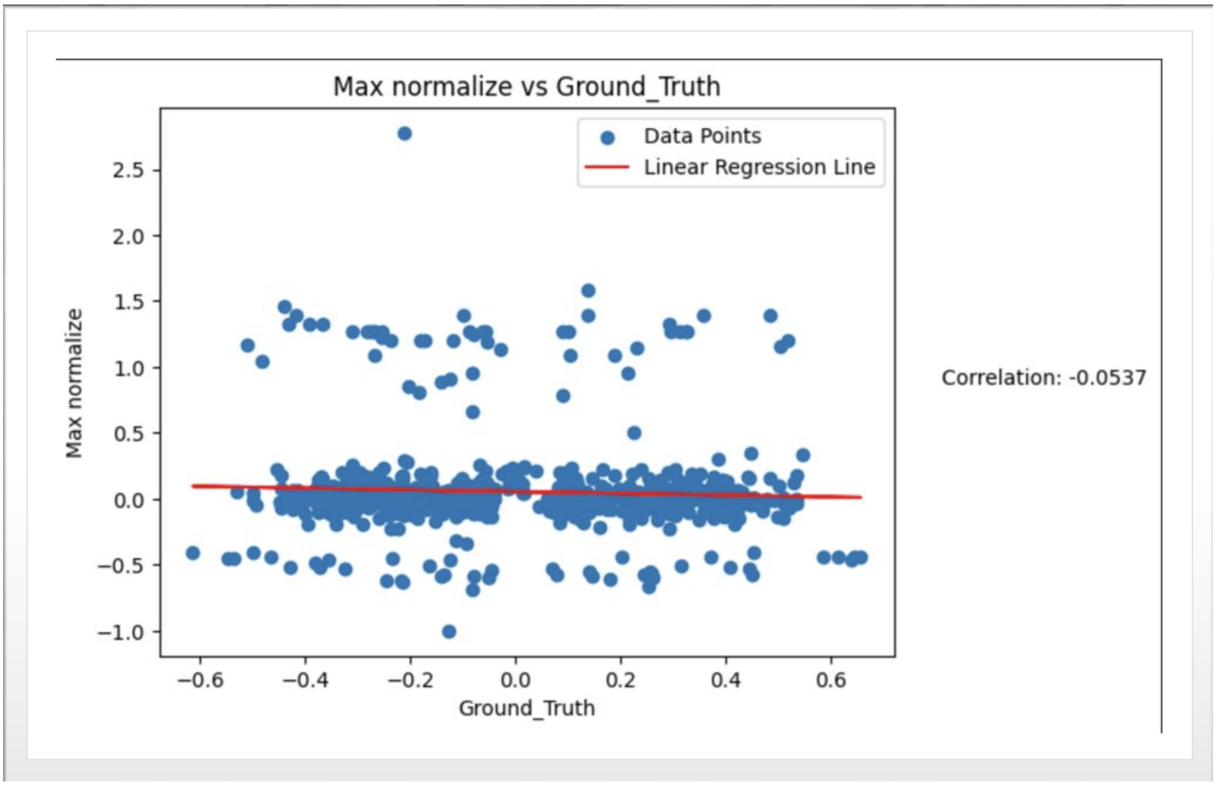


Figure 4.5: Feature - Max

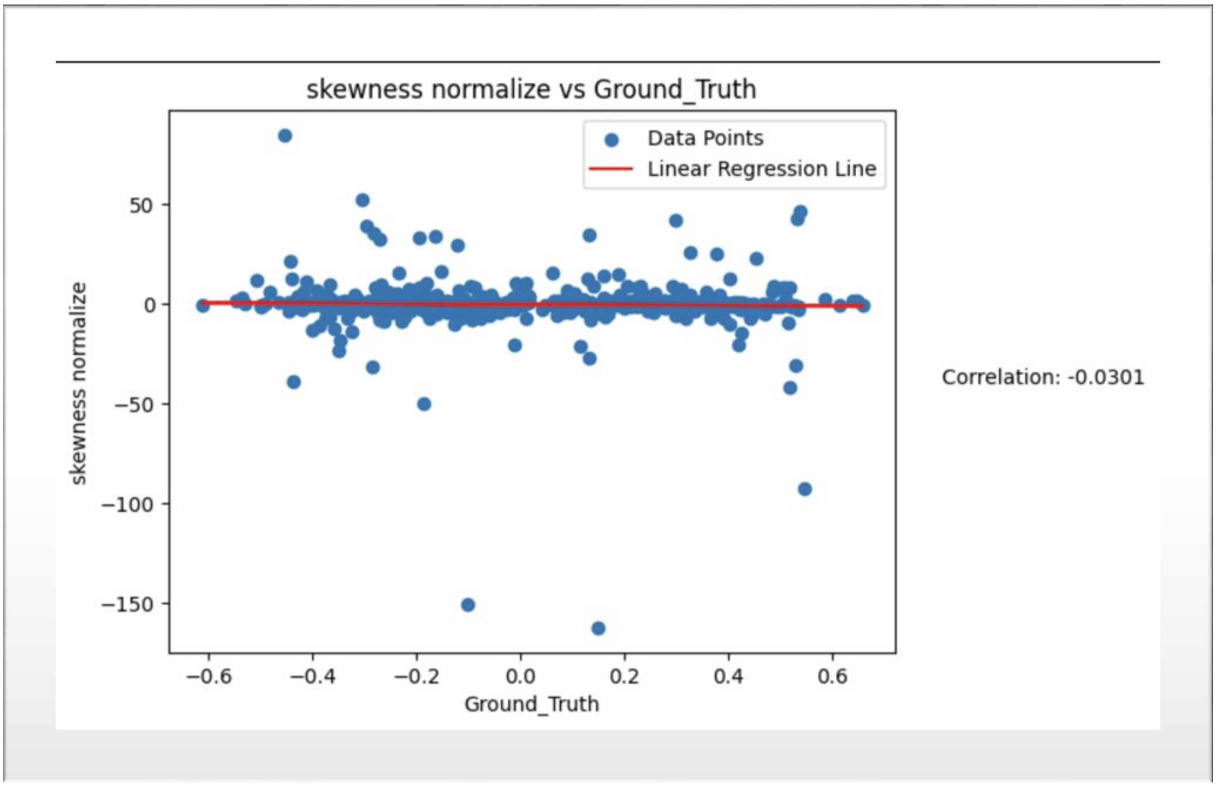


Figure 4.6: Feature - Skewness

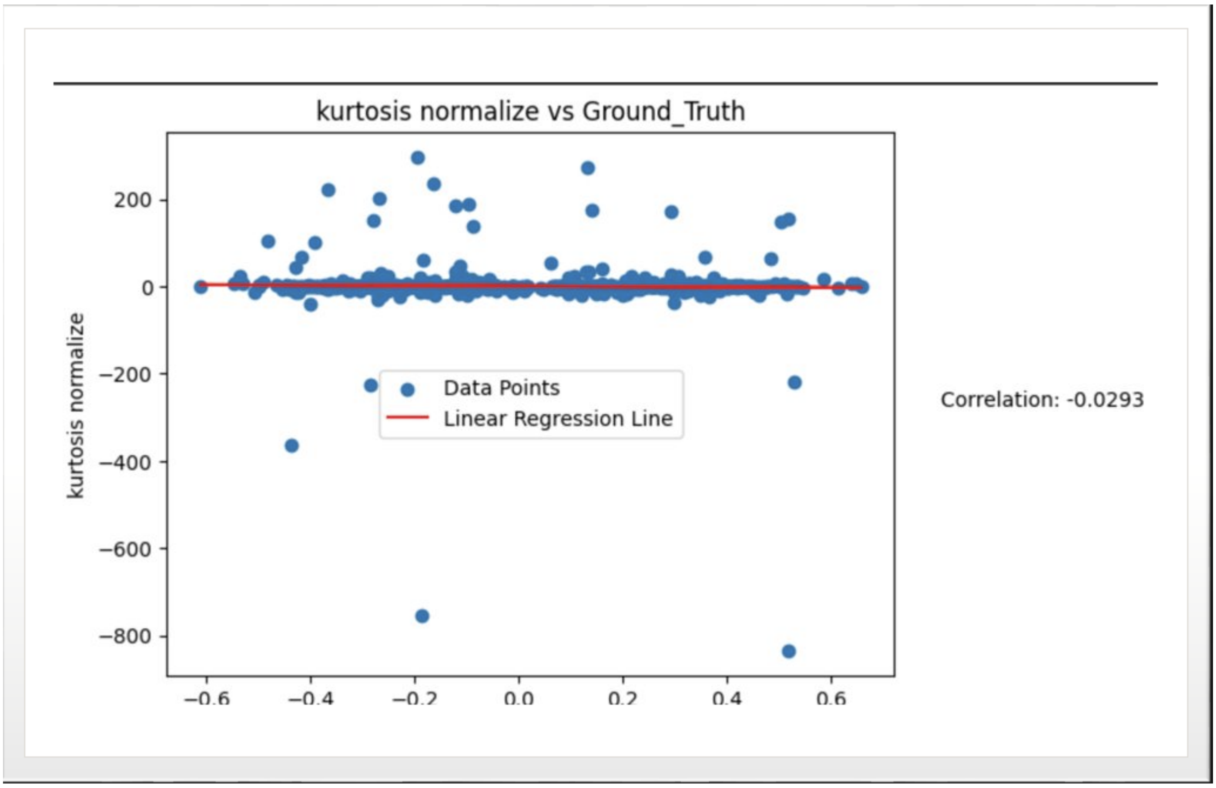


Figure 4.7: Feature - Kurtosis

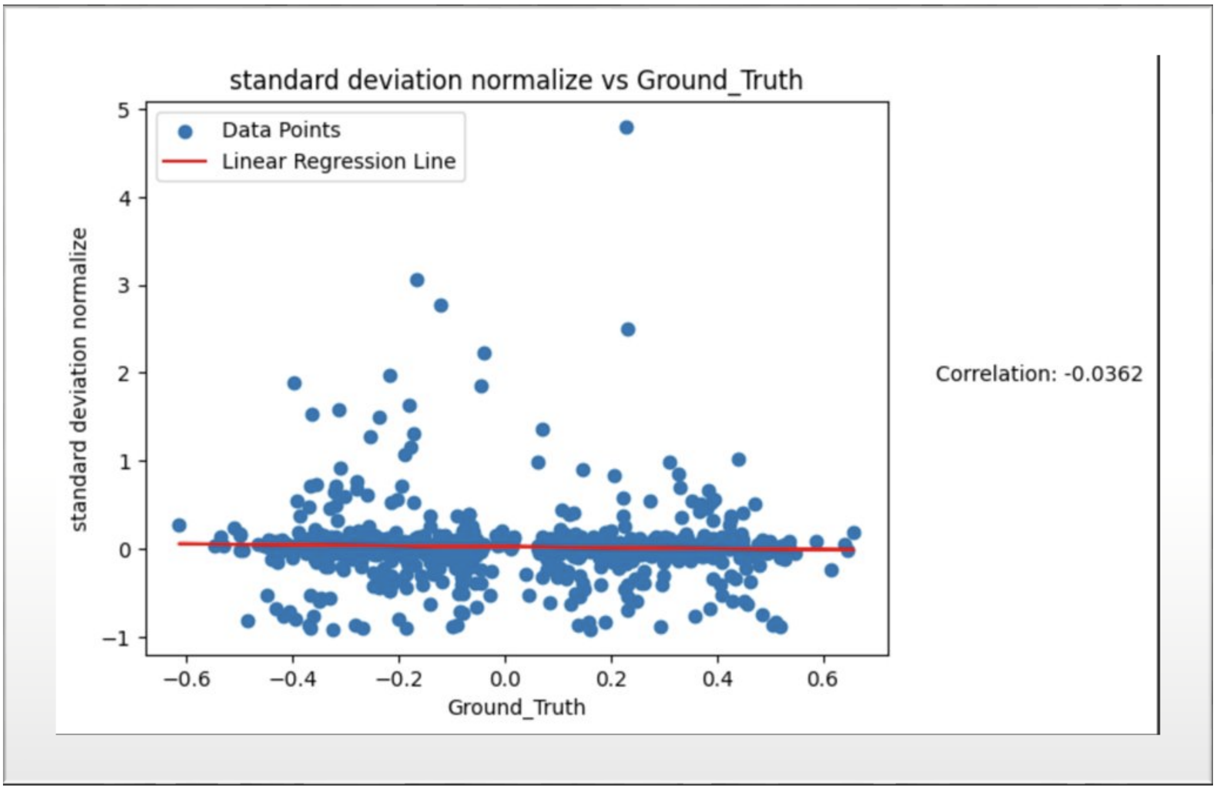


Figure 4.8: Feature - Standard Deviation

4.5 Investigation

Investigation was done and lot of missing values were found, such as the blue-tooth got disconnected for the shimmer device and hence the data for the heart-rate could not be recorded for some of the participants.

The heart-rate data was also not accurate for many of the participants as there were multiple missing values in the dataset and hence which plotting the graphs, the graphs did not come accurate and also the correlation did not come as desired.

Even the regression was not showing for std due to multiple nan values. Therefore, interpolation was done to fill in the missing values to get better results while plotting the graphs.

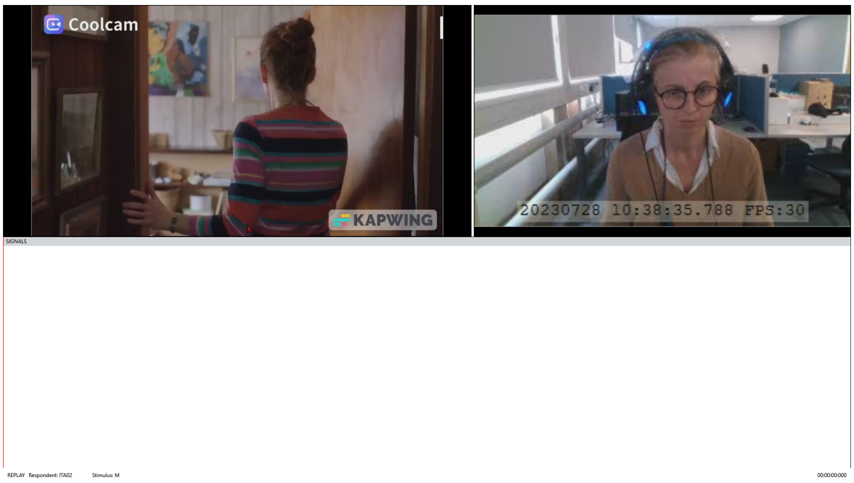


Figure 4.9: Participant with data not recorded

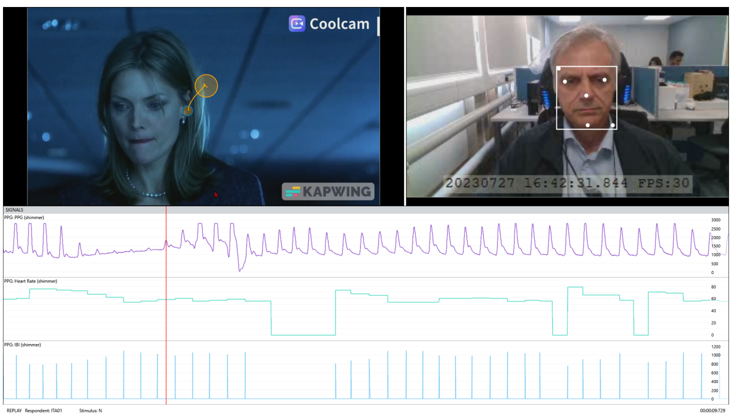


Figure 4.10: The straight lines in the graph indicate missing values

4.6 Data-set before and after interpolation

Heart Rate P	IBI PPG ALG
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1
64	-1

Figure 4.11: Graph plotted on the original data-set

VS

Heart Rate P	IBI PPG ALG
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
64	778.739517
67.5	778.739517
71	835.9375
71	835.441468
71	834.945437
71	834.449405
71	833.953373
71	833.457341
71	832.96131
71	832.465278
71	831.969246
71	831.473214
71	830.977183
71	830.481151
71	829.985119
71	829.489087
71	828.993056

Figure 4.12: Graph plotted after doing the interpolation

4.6.1 Graphs

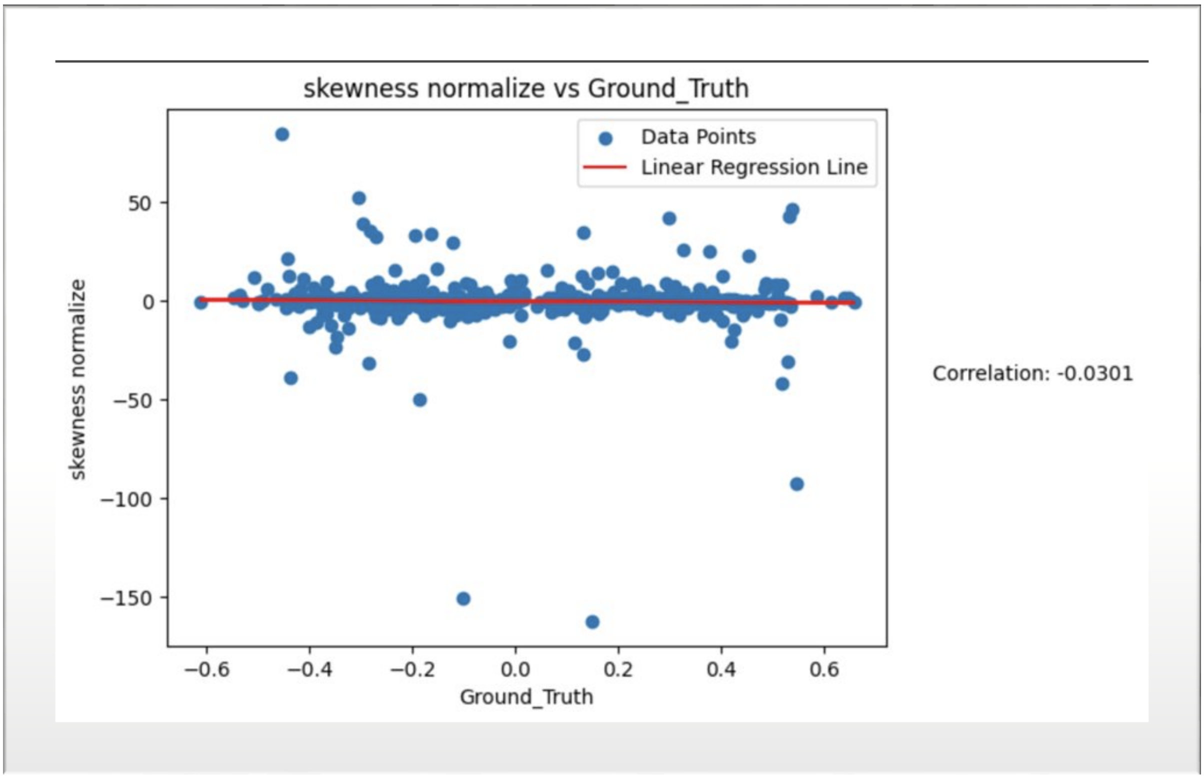


Figure 4.13: Values shown of the original data-set
VS

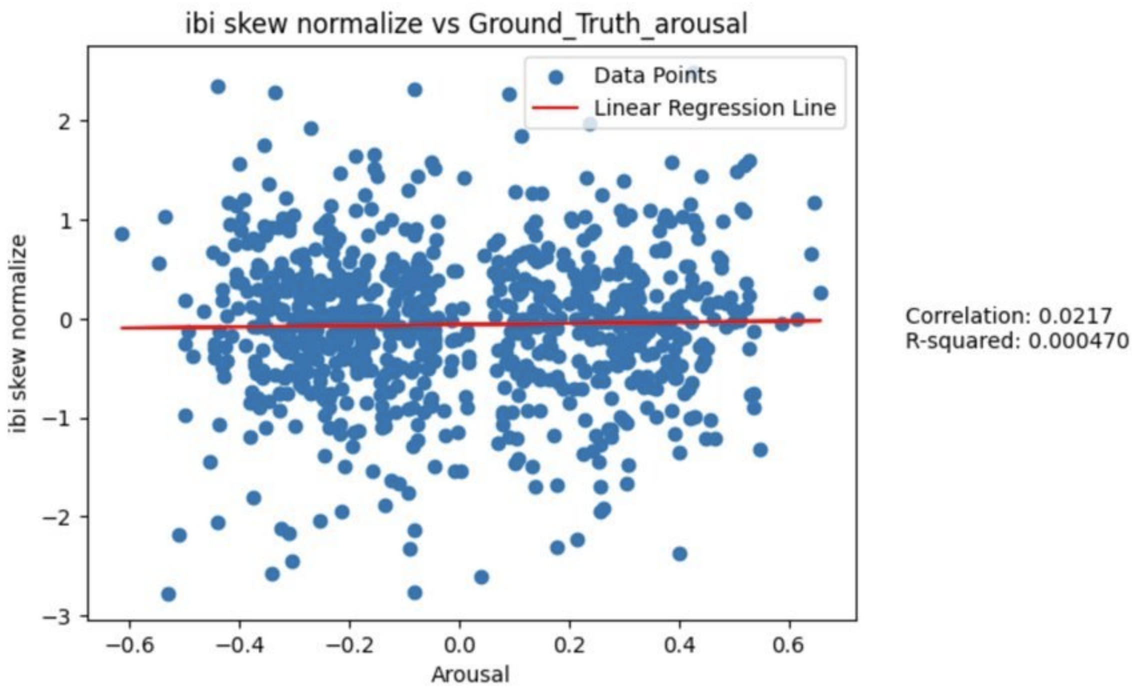


Figure 4.14: Values shown after interpolation was done

4.7 Graphs plotted for all features (Correlation 1)

4.7.1 Inter-beat Interval (IBI) and Heart Rate (HR)

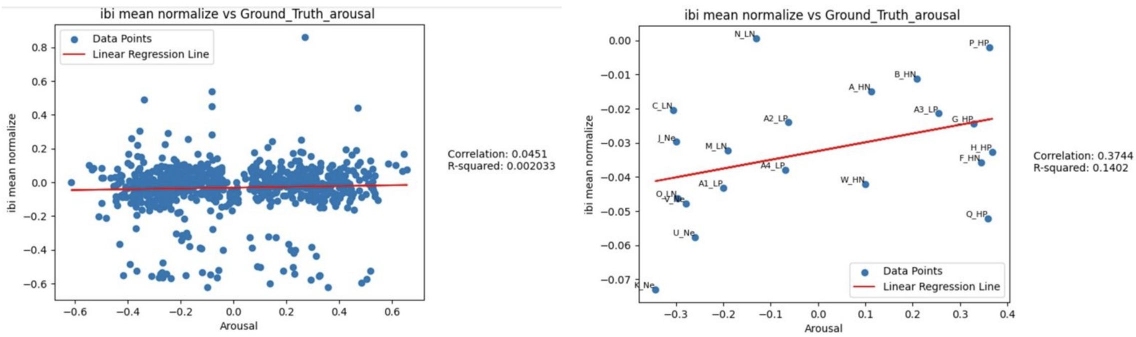


Figure 4.15: IBI Feature - Mean

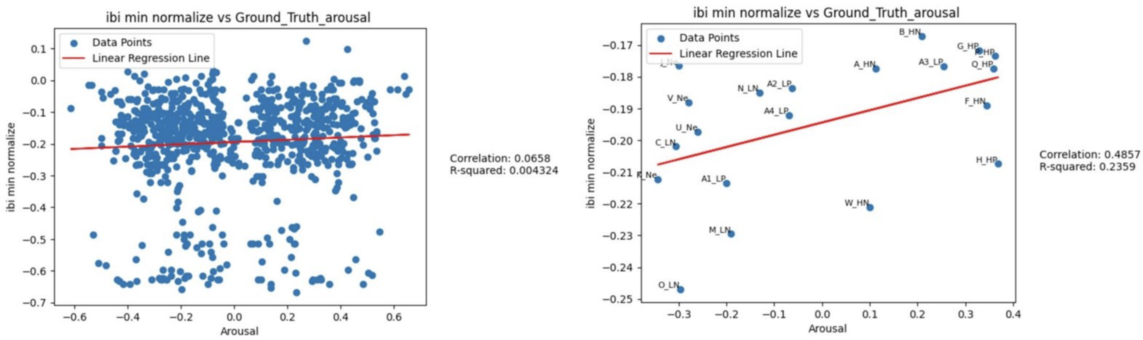


Figure 4.16: IBI Feature - Min

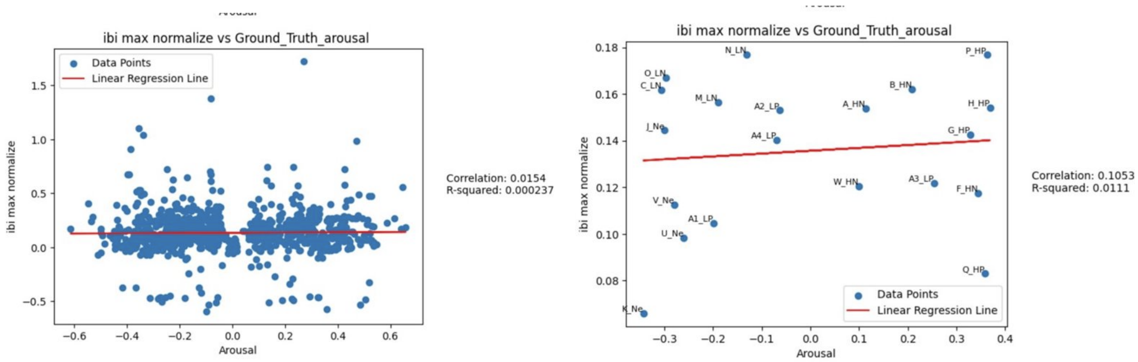


Figure 4.17: IBI Feature - Max

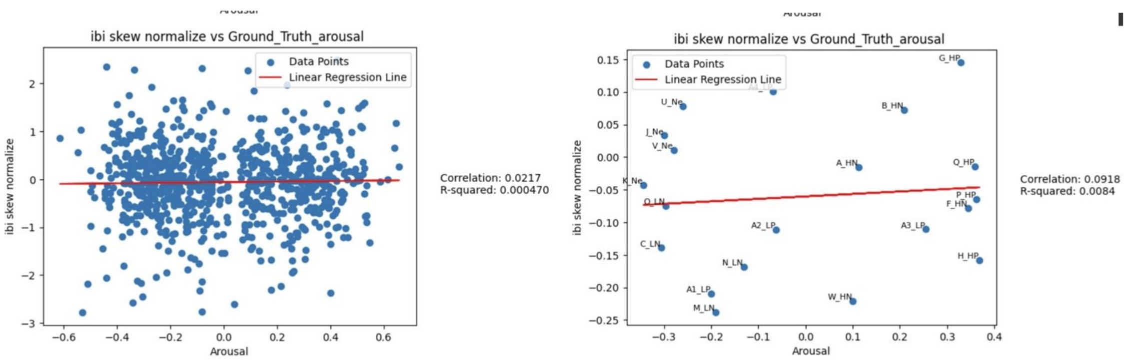


Figure 4.18: IBI Feature - Skewness

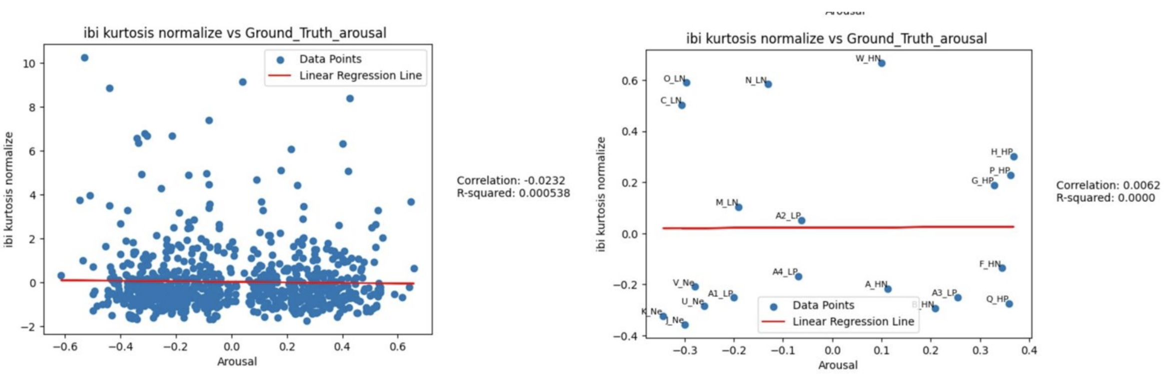


Figure 4.19: IBI Feature - Kurtosis

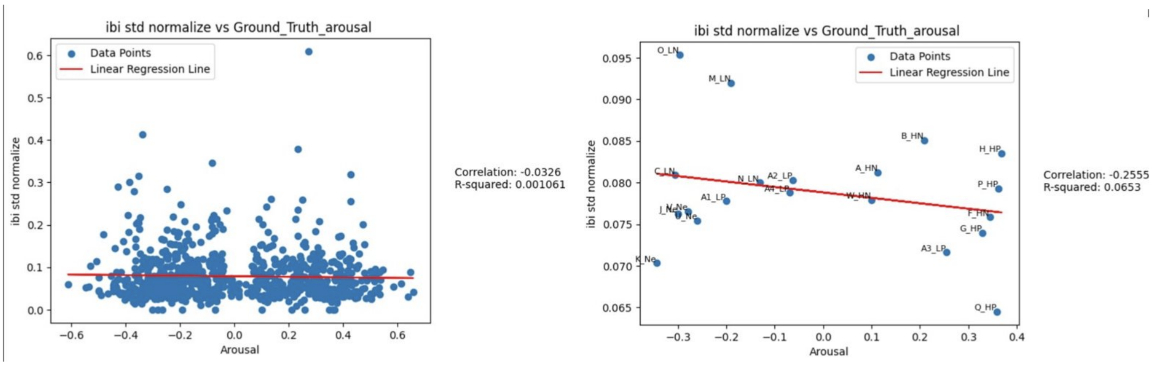


Figure 4.20: IBI Feature - Standard Deviation

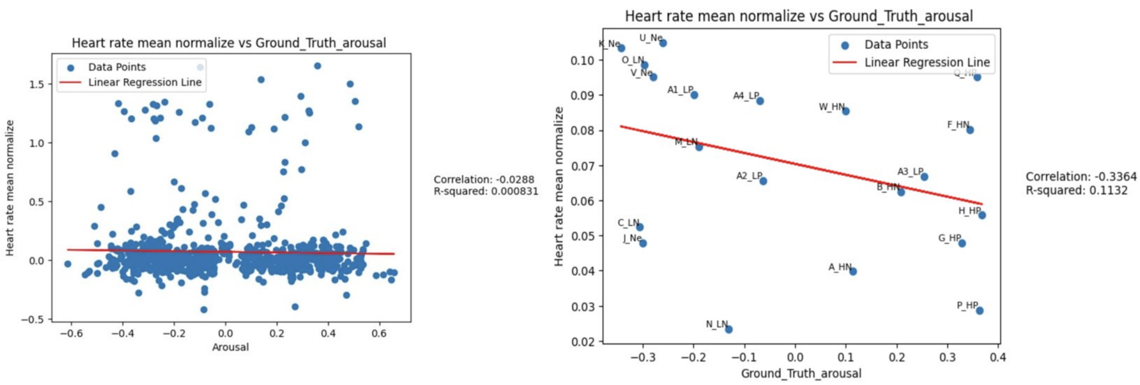


Figure 4.21: HR Feature - Mean

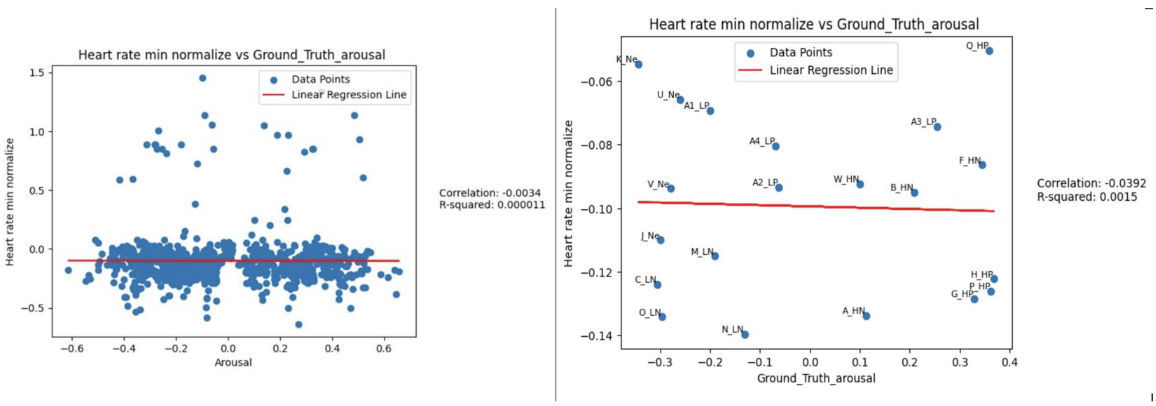


Figure 4.22: HR Feature - Min

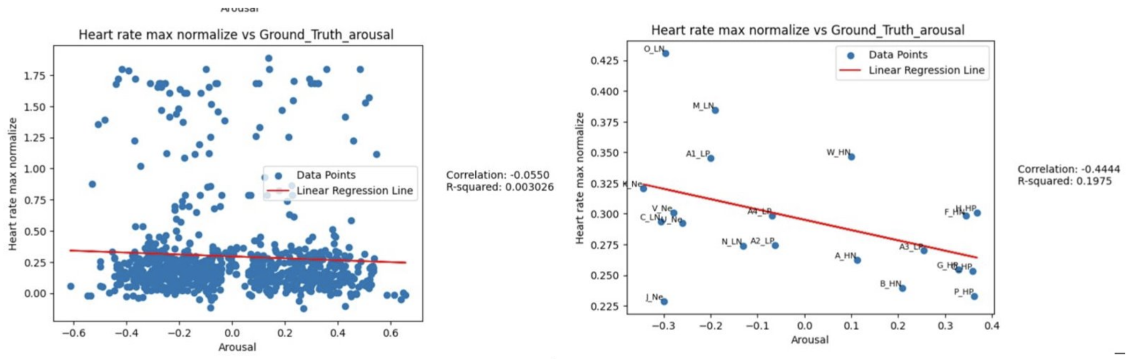


Figure 4.23: HR Feature - Max

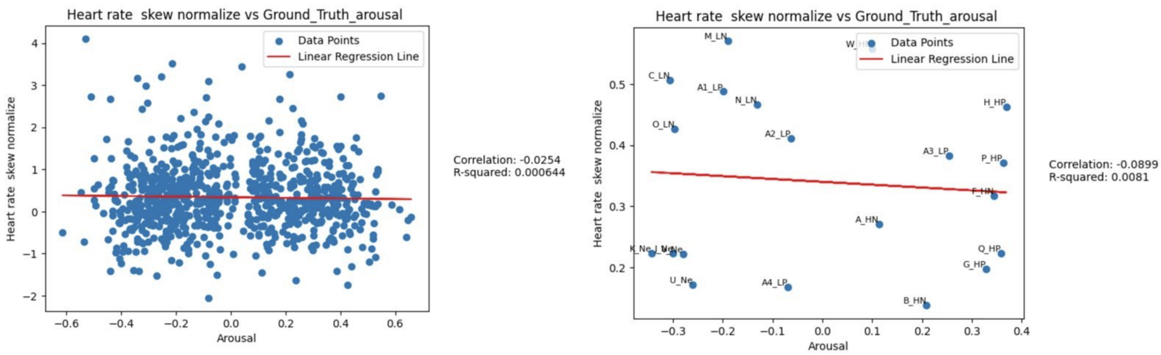


Figure 4.24: HR Feature - Skewness

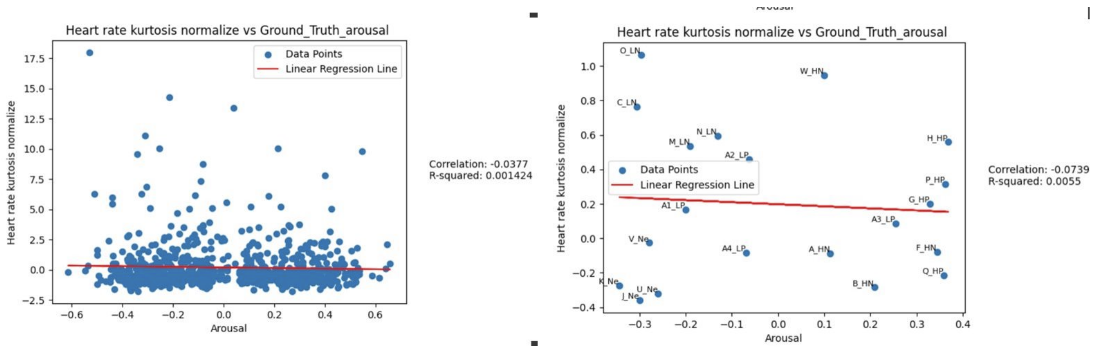


Figure 4.25: HR Feature - Kurtosis

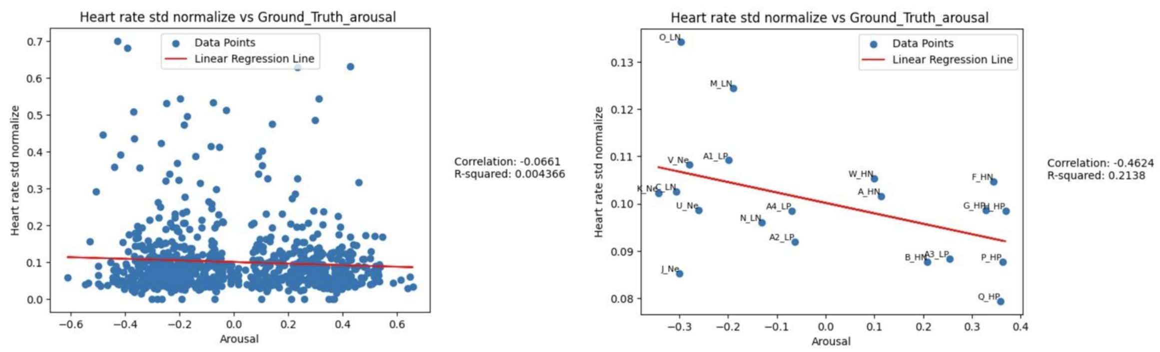


Figure 4.26: HR Feature - Standard Deviation

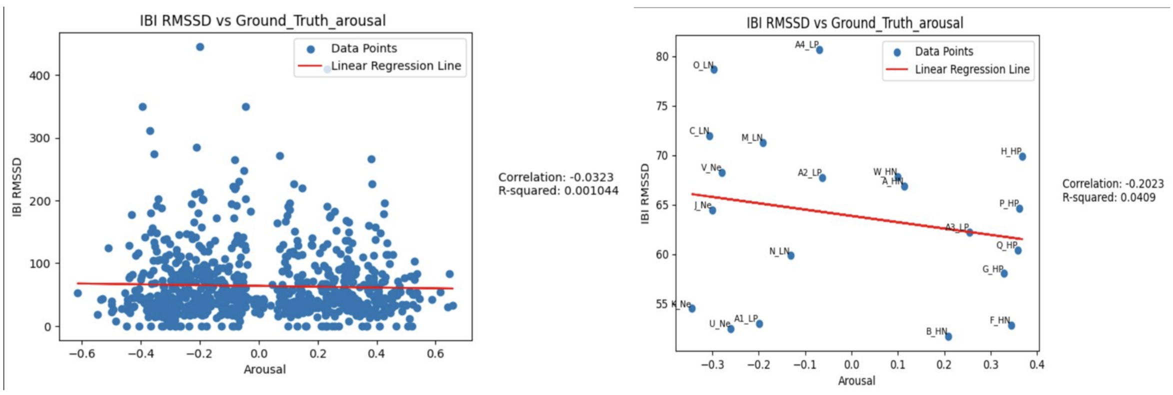


Figure 4.27: HR Feature - Rmssd

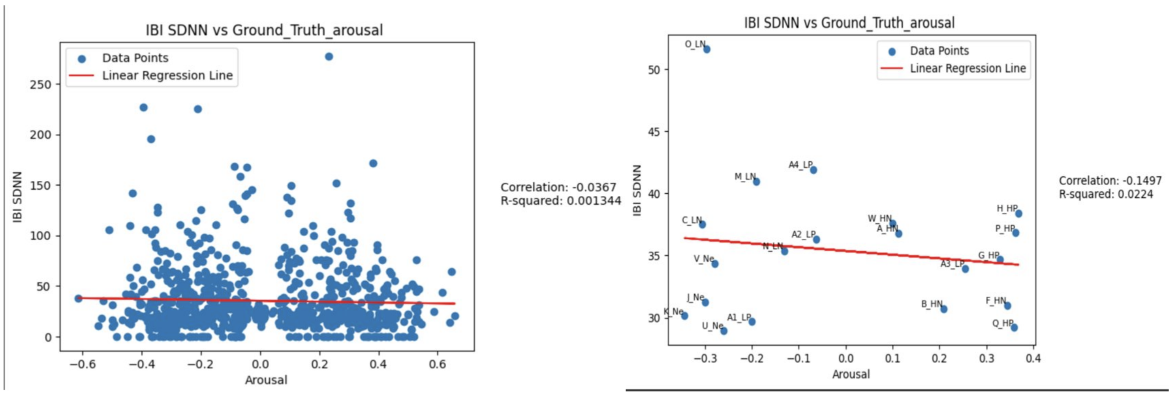


Figure 4.28: HR Feature - Sdnn

4.8 Graphs plotted for all features (Correlation 2)

4.8.1 Inter-beat Interval (IBI) and Heart Rate (HR)

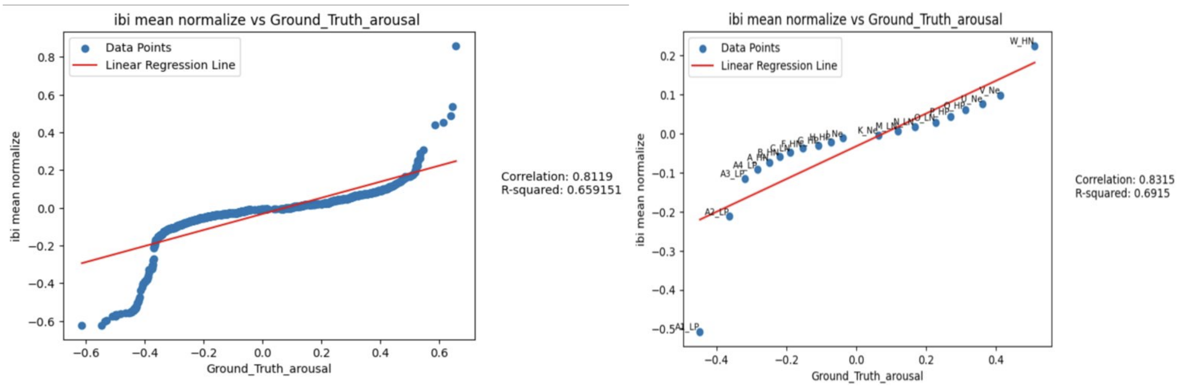


Figure 4.29: IBI Feature - Mean

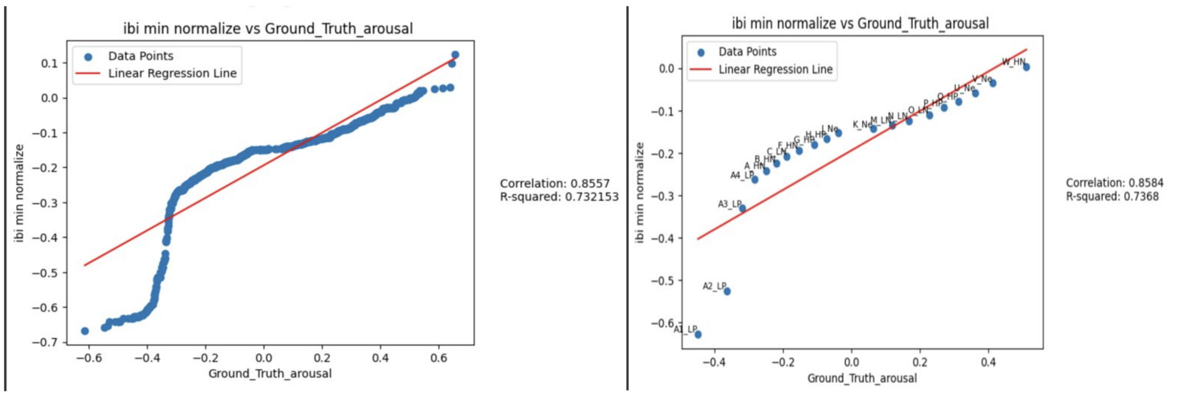


Figure 4.30: IBI Feature - Min

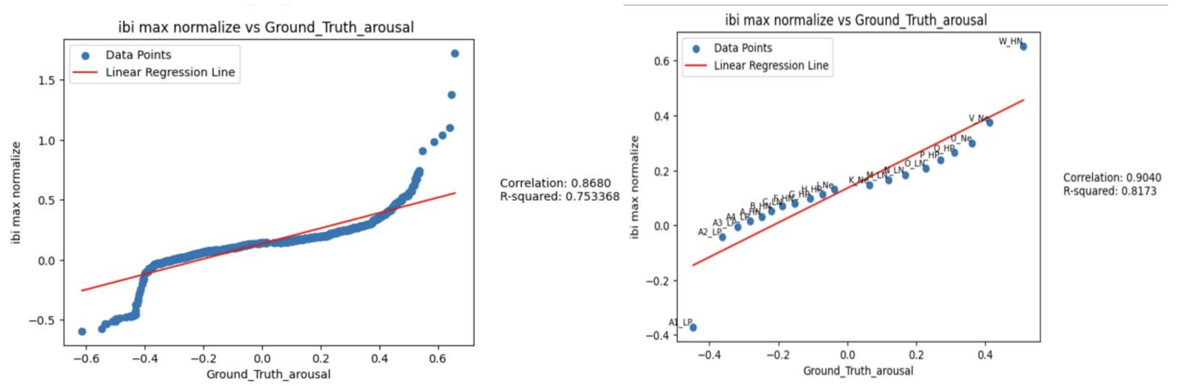


Figure 4.31: IBI Feature - Max

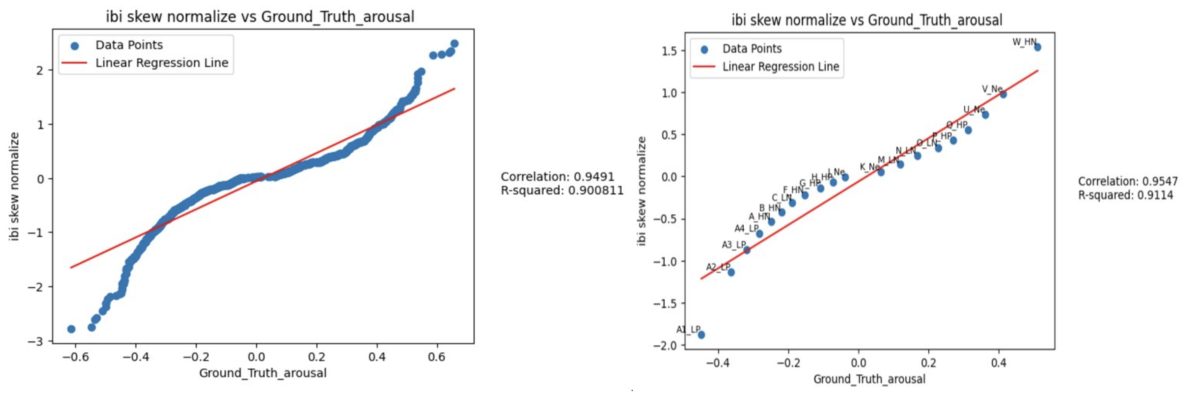


Figure 4.32: IBI Feature - Skewness

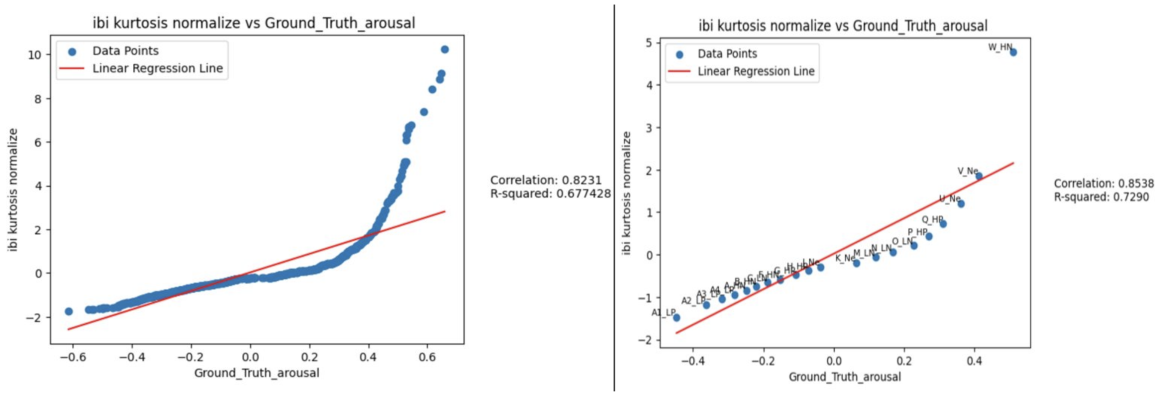


Figure 4.33: IBI Feature - Kurtosis

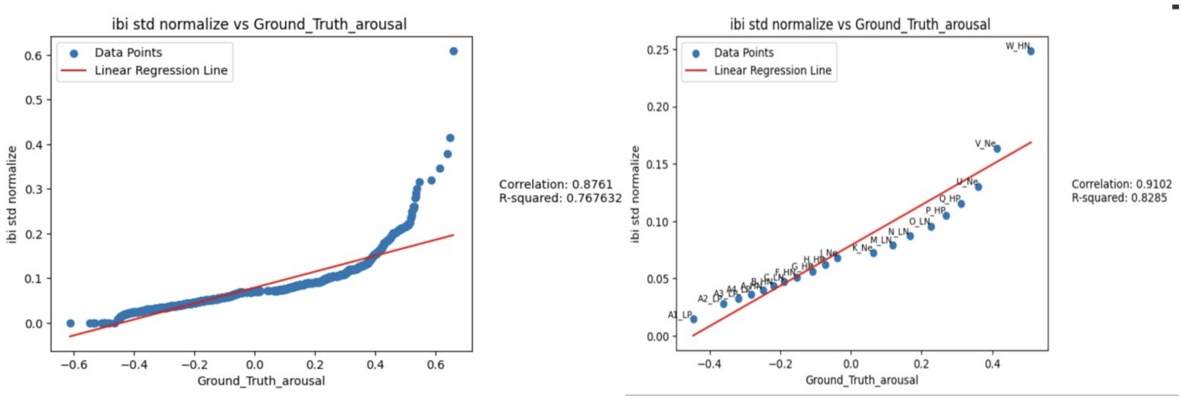


Figure 4.34: IBI Feature - Standard Deviation

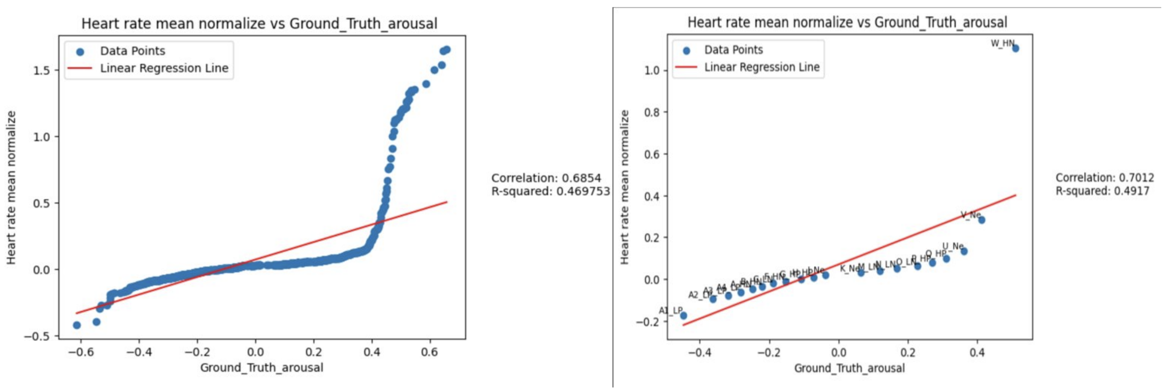


Figure 4.35: HR Feature - Mean

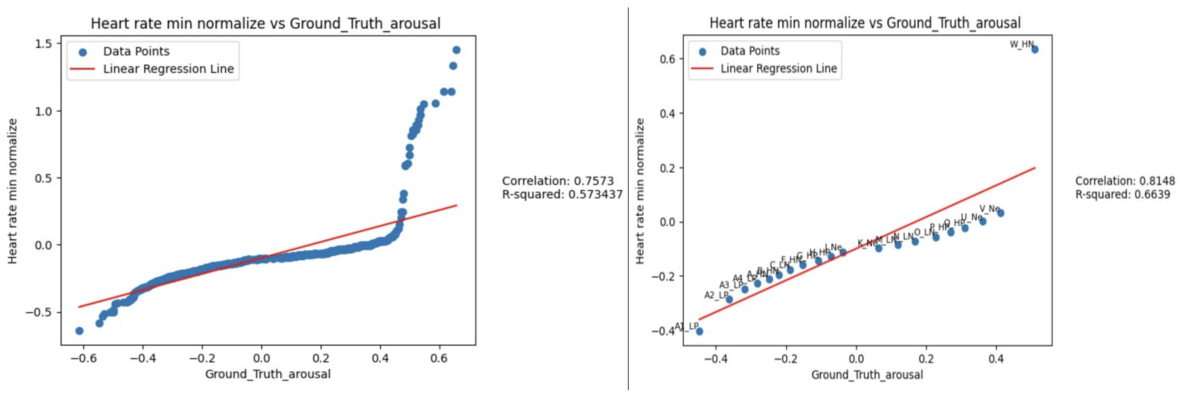


Figure 4.36: HR Feature - Min

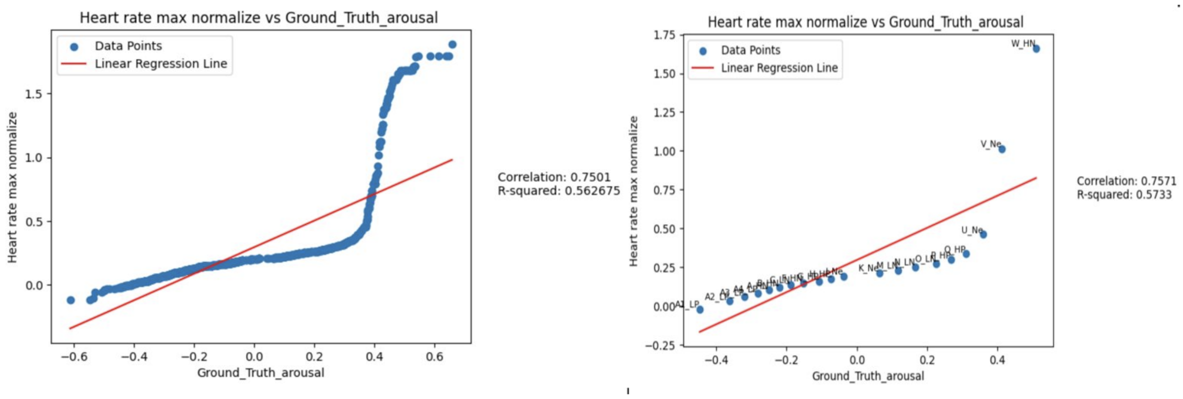


Figure 4.37: HR Feature - Max

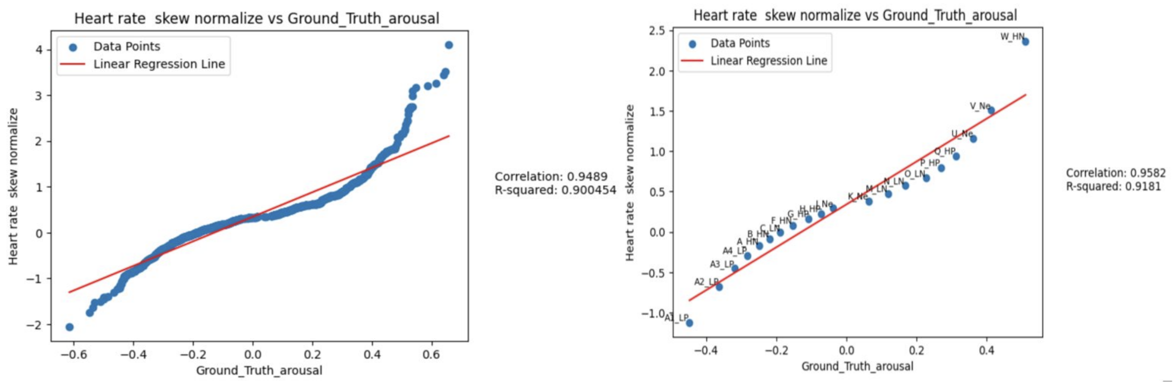


Figure 4.38: HR Feature - Skewness

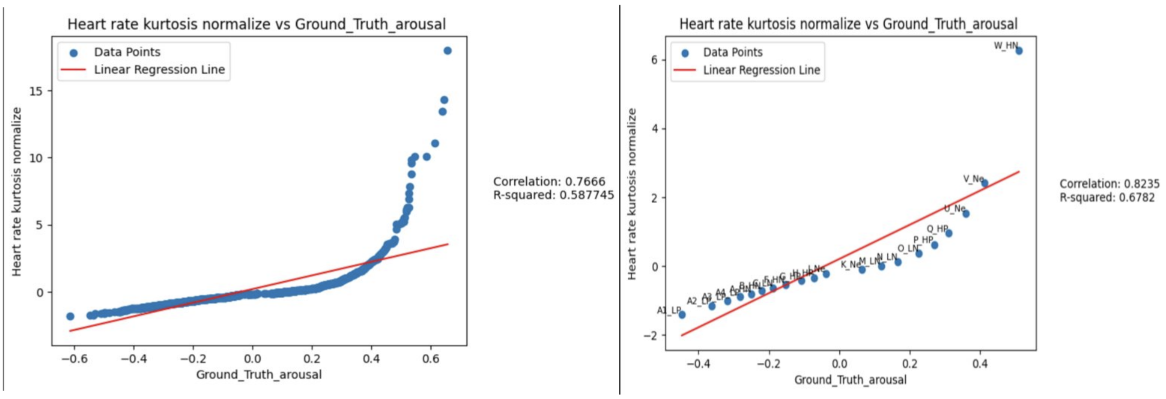


Figure 4.39: HR Feature - Kurtosis

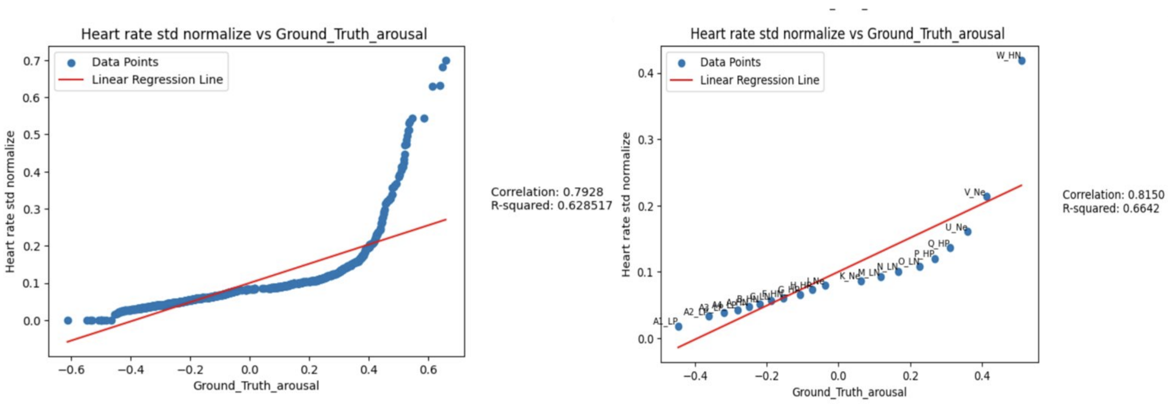


Figure 4.40: HR Feature - Standard Deviation

CHAPTER 5

Conclusion

To sum up, this study has effectively shown that heart rate variability (HRV) is a reliable indicator of arousal during transcranial magnetic stimulation (TMS). We found that five out of six subjects showed periods of decreased arousal through rigorous data collection and sophisticated analysis using imotions software, highlighting the sensitivity of HRV to changes in arousal states. Future research will benefit greatly from these findings, especially when it comes to continuously gathering heart rate data during TMS to better understand the connection between arousal states and TMS-induced data changes. Furthermore, by using machine learning techniques to process data from various physiological sensors, the primary goal of this research analyzing physiological signals for investigating emotional arousal and stress levels was achieved, improving our understanding of the autonomic nervous system.

The study also poses interesting research questions regarding the relationship between HRV and various emotional states, the ability to interpret complex emotional states by combining heart rate data with psychological measures, and the efficiency of the iMotions software in differentiating between stress levels and real-time heart rate monitoring for biofeedback applications. The potential of HRV and iMotions software in clinical settings, particularly for stress management therapy and the development of biofeedback techniques to treat conditions like anxiety, is highlighted by these questions in addition to paving the way for future research.

5.1 Future Work

Looking ahead, this study suggests a number of interesting directions for further research. First and foremost, increasing the sample size would be helpful in validating the HRV analysis during a larger population, which would improve the findings' generalizability. One subject's consistently high arousal levels also highlight the urgent need to explore individual variability in order to better understand the complexities of HRV as a measure of arousal and its implications for personalized medicine. Furthermore, a deeper comprehension of complex emotional states is anticipated through the integration of HRV with a greater range of physiological and psychological measures. This multifaceted method might reveal subtle relationships between different emotional states and their physiological indicators.

Further research is necessary to fully explore the potential of iMotions software for real-time heart rate monitoring for biofeedback applications. Subsequent investigations may concentrate on formulating procedures that maximize the application of iMotions for biofeedback training and real-time data analysis. Such studies may have important therapeutic ramifications, especially for the management of disorders associated with stress. Furthermore, using HRV and other physiological measurements, machine learning models can be improved to improve the accuracy of stress level differentiation. The combination of these sophisticated computational methods with reliable physiological data may result in significant advancements in the analysis of emotional states and biometric monitoring. Therefore, these paths hold great promise for both practical applications in healthcare and psychological well-being as well as exciting opportunities for academic research.

5.2 Appendix

Code Links

https://github.com/Assassins7blade/CE901---Dissertation.git

All my codes are provided in the link above and in my github.

Bibliography

[1] Kristina Schaaff and Marc T. P. Adam, "PoincarÃ© plot for 5 minutes of ECG data during baseline," in *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, 2013, p. 251. DOI: 10.1109/ACII.2013.66.

[2] Kristina Schaaff and Marc T. P. Adam, "The Yerkes-Dodson-Law," in *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, 2013, p. 251. DOI: 10.1109/ACII.2013.66.

[3] Kristina Schaaff and Marc T. P. Adam, "Mean Values and staandard deaviations," in *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, 2013, p. 251. DOI: 10.1109/ACII.2013.66.

[4] Kristina Schaaff and Marc T. P. Adam, "Fisher's Discriminant ratio for all features," in *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, 2013, p. 251. DOI: 10.1109/ACII.2013.66.

[5] Magrupov, T., Magrupova, M., Abdihalikov, S. (2020). "Elimination of baseline deviation. Comparison of the signal before and after filtering." In *Proceedings of the 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, p. 251. DOI: 10.1109/ACII.2013.66.

[6] Alberdi, A. Aztiria and A. Basarab, âTowards an automatic early stress recognition system for office environments based on multimodal measurements: A reviewâ, Journal of Biomedical Informatics, vol. 59, pp. 49â75, February, 2016.

[7] M. Faezipour, A. Saeed, S.C. Bulusu, M. Nourani, H. Minn and L. Tamil, âA patient-adaptive profiling scheme for ECG beat classificationâ, IEEE Transactions on Information Technology in Biomedicine, vol 14 (5), pp.1153â1165, June, 2010.

[8] M. Nirupama, ECG noise cancellation using RLS adaptive filter. Middle East J. Sci. Res., vol. 18(12), pp. 1807â1811, 2013.

[9] M. Abo-Zahhad, âECG signal compression using discrete wavelet transformâTheory and applicationsâ, Discrete Wavelet Transform, pp. 143â168, April, 2011.

[10] Mohamed Hammad, Asmaa Maher, Kuanquan Wang, Feng Jiang and Moussa Amrani, âDetection of abnormal heart conditions based on characteristics of ECG signalsâ, Measurement, vol 125, pp. 634-644, September, 2018.

[11] W. Jiang and S.G. Kong, âBlock-Based neural networks for personalized ECG signal classificationâ, IEEE Transactions Neural Network, vol 18(6), pp. 1750â1761, November, 2007.

[12] S.Z. Mahmoodabadi, A. Ahmadian and M.D. Abolhasani, âECG feature extraction using daubechies waveletsâ, International Conference Visualization, Imaging and Image Processing, pp. 343- 348, Benidorm, September, 2005.

[13] Posner, J., Russell, J. A., Peterson, B. S. (2005). The circumplex model of affect: an integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and Psychopathology, 17(3), 715-734. doi: 10.1017/S0954579405050340. PMCID: PMC2367156. Thecircumplexmodelofaffect: anintegrativeapproachtoaffectiveneuroscience, cognitivedevelopment, andpsychopathology-PubMed

[14] I. Odinaka, L. Po-Hsiang, A.D. Kaplan, J.A. OâSullivan, E.J. Sirevaag and J.W. Rohrbaugh, âECG biometric recognition: A comparative analysisâ, IEEE Transactions Information Forensics Security, vol 7(6), pp. 1812â1823, December, 2012.

[15] Inderbir Kaur, Rajni Rajni and Anupma Marwaha, âECG signal analysis and arrhythmia detection using wavelet transformâ, Journal of The Institution of Engineers (India), vol 9(4), pp.499-507, December, 2016.

[16] Posner, J., Russell, J. A., Peterson, B. S. (2005). The circumplex model of affect: an integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and

Psychopathology, 17(3), 715-734. doi: 10.1017/S0954579405050340. PMCID: PMC2367156. Thecircumplexmodelofaffect: anintegrativeapproachtoaffectiveneuroscience, cognitivedevelopment,andpsychopathology-PubMed

[17] Javorka M, Zila I, BalhÃ¡rek T and Javorka K., âHeart rate recovery after exercise: relations to heart rate variability and complexityâ, Brazilian Journal of Medical and Biological Research, vol 35(8), pp. 991-1000, August, 2002.

[18] G. Vega-MartÃnez, C. Toledo-Peral, C. Alvarado-Serrano, L. Leija Salas, O. G. Aztati-Aguilar and A. de Vizcaya-Ruiz, "SDNN index of heart rate variability as an indicator of change in rats exposed to fine particles: study of the impact of air pollution in Mexico City", International Conference on Electrical Engineering, Computing Science and Automatic Control, pp. 1-4, Campeche, September-October, 2014.

[19] Rishi Raj Sharma and Ram Bilas Pachori, âBaseline wander and power line interference removal from ECG signals using eigenvalue decompositionâ, Biomedical Signal Processing and Control, Vol 45, pp. 33-49, August 2018.

[20] S.K. Yadav, R. Sinha and P.K. Bora, âElectrocardiogram signal denoising using non-local wavelet transform domain filteringâ, IET Signal Processing, vol. 9, pp. 88â96, December, 2015.

[21] Jakub S. GÄsior, Jerzy Sacha, Piotr J. JeleÅ, Jakub ZieliÅski and Jacek Przybylski âHeart rate and respiratory rate influence on heart rate variability repeatability: Effects of the correction for the prevailing heart rateâ, vol 7, pp. 1-11, August, 2016.

[22] Kumar, P., Das, A. K., Halder, S. (2018). Early and Later Post-Exercise Heart Rate Variability Analysis of ECG Signal, IEEE. Figure 1.

[23] Kumar, P., Das, A. K., Halder, S. (2018). Early and Later Post-Exercise Heart Rate Variability Analysis of ECG Signal, IEEE. Figure 6.

[24] Kumar, P., Das, A. K., Halder, S. (2018). Early and Later Post-Exercise Heart Rate Variability Analysis of ECG Signal, IEEE. Figure 7.

[25] Kumar, P., Das, A. K., Halder, S. (2018). Early and Later Post-Exercise Heart Rate Variability Analysis of ECG Signal, IEEE. Figure 10.

[26] G.W. Jenkins, C.P. Kemnitz, and G.J. Tortora, Anatomy and Physiology From Science to Life, Hoboken, NJ: John Wiley Sons, Inc., 2007, pp. 532-533, 709-717.

[27] M.A. Conny, et al, âHeart Rate Variability,â Annals of Internal Medicine, vol. 118, pp. 436- 447, 1993

[28] K.L. McCance, and S.E. Huether, Pathophysiology: The Biologic Basis for Disease in Adults, 5th ed. St. Louis, MO: Elsevier Mosby, 2006, pp. 1048-1049

[29] P.K. Stein, M.S. Bosner, R.E., Kleiger, and B.M. Conger, âHeart rate variability: A measure of cardiac autonomic tone,â American Heart Journal, vol.127, no. 6, pp. 1376-1381, 1994.

[30] E.H. Hon, and S.T. Lee, âElectronic evaluations of the fetal heart rate. VIII. Patterns preceding fetal death, further observations. American journal of obstetrics and gynecology, vol 87, pp. 814-816, 1965.

[31] M. Malik, âHeart rate variability Standards of measurement, physiological interpretation, and clinical use,â European Heart Journal, vol. 17, pp. 354-381, 1996.

[32] M.P. Griffin, T.M. OâShea, E.A., Bissonette, F.E. Harrell, D.E. Lake, and J.R. Moorman, âAbnormal Heart Rate Characteristics Preceeding Neonatal Sepsis and Sepsis-Like Illness,â Pediatric Research, vol. 53, no. 6, pp. 920-926, 2003.

[33] M.P. Griffin, and J.R. Moorman, âToward the Early Diagnosis of Neonatal Sepsis and Sepsis- Like Illness Using Novel Heart Rate Analysis,â Pediatrics, vol 107, no. 1, pp. 97-104, 2001.

[34] A. Murata, Y. Hiramatsu, âEvaluation of Drowsiness by HRV Measures â Basic Study for Drowsy Driver Detection,â in Conf. Rec. 2009 IEEE Fourth International Workshop on Computational Intelligence Applications, pp. 99-102.

[35] T. Kujirai, et al, âCorticocortical inhibition in human motor cortex,â Journal of Physiology, vol. 47, pp. 501-519, 1993

[36] R. Chen, et al, âMechanisms of cortical reorganization in lower-limb amputees,â Journal of Neuroscience, vol. 18, no. 9, pp. 3443-3450, 1998.

[37] K.M.Jacobs,J.P.Donoghue,âReshapingthecorticalmotormapby unmasking latent intracortical connections,â Science, vol. 251, no. 4996, pp. 944-977, 1991.

[38] J. Liepert, et al, âExercise-induced changes of motor excitability with and without sensory block,â Brain Research, vol. 1003, no. 1-2, pp. 68-76, 2004.

[39] M.C. Ridding, J.C. Rothwell, âAfferent input and cortical organisation: a study with magnetic stimulation,â Experimental Brain Research, vol. 126, no. 4, pp. 536-544, 1999.

[40] H. Haavik-Taylor, B. Murphy, âTransient modulation of intracortical inhibition following spinal manipulation,â Chiropractic Journal of Australia, vol. 37, pp. 106-116, 2007.

[41] N. Watanabe, J. Reece, B.I. Polus, âEffects of body position on autonomic regulation of cardiovascular function in young, healthy adults,â Chiropractic Osteopathy, vol. 15, 2007.

[42] C. McGregor, et al, âCollaborative Research on an Intensive Care Decision Support System utilizing Physical Data Streams (Published Symposium Proceedings style),â in AMIA Symposium Proceedings, 2009, pp. 1124-1126.

[43] M. Blount, et al, âReal-Time Analysis for Intensive Care: Development and Deployment of the Artemis Analytic System,â IEEE Engineering in Medicine and Biology Society Magazine, pp. 110- 118. 2010.

[44] Goldie, J., McGregor, C., Murphy, B. (2010). Determining Levels of Arousal using Electrocardiography: A study of HRV during Transcranial Magnetic Stimulation. In Proceedings of the 32nd Annual International Conference of the IEEE EMBS

[45] Goldie, J., McGregor, C., Murphy, B. (2010). Determining Levels of Arousal using Electrocardiography: A study of HRV during Transcranial Magnetic Stimulation. In Proceedings of the 32nd Annual International Conference of the IEEE EMBS. IEEE. [Figure 2].

[46] R. Sameni et al. âA nonlinear Bayesian filtering framework for ECG denoising,â IEEE Transactions on Biomedical Engineering 2007 vol. 54, no. 12. â pp. 2172 â 2185.

[47] R. M. Rangayyan, John Wiley Sons, âBiomedical signal analysis,â 2015.

[48] C. N. Bairey Merz, O. Elboudwarej, and P. Mehta, âThe autonomic nervous system and cardiovascular health and disease. A complex balancing act,â JACC: Heart Failure, vol. 3, no. 5, pp. 383-385, 2015.

[49] Heart rate variability // Kardi.ru. URL:http://www.kardi.ru/ru/index/ Article?Id=37ViewType=view/.

[50] G. Moldabek, âHeart rate variability indicators in patients with hypothyÂ¬$roidism, MedicalandHealthScienceJournal, vol.6, pp.127 - 131, 2011.$

[51] F. Shaffer and J. P. Ginsberg, â An Overview of Heart Rate Variability Metrics and Norms,â Frontiers in Public Health, vol. 5, no. September, pp. 1-17, 2017.

[52] B. N. Singh, A. K. Tiwari, âOptimal selection of wavelet basis function applied to ECG signal denoising,â Digital Signal Processing, vol. 16, no. 3, 2006, pp. 275â287.

[53] S.-W. Chen, H.-C. Chen, H.-L. Chan, âA real-time QRS detection method based on moving-averaging incorporating with wavelet denoising,â Computer Methods and Programs in Biomedicine, vol. 82, no. 3, 2006, pp. 187â195.

[54] Heart rate variability. Measurement standards, physiological interpretation and clinical use Working group of the European Heart Society and the North American Society of Stimulation and Electrophysiology URL:https://www.incart.ru/assets/pdf/hrv-standards.pdf.

[55] S. Luo, P. Johnston âA review of electrocardiogram filtering,â Journal Electrocardiol, 2010; 43(6), pp. 486â496.

[56] Biederman J, Spencer T. Attention-deficit/hyperactivity disorder (ADHD) as a noradrenergic disorder. Biological Psychiatry. 1999;46:1234â1242. [PubMed] [GoogleScholar]

[57] Blumberg H, Kaufman J, Martin A, Whiteman R, Gore J, Charney D, Krystal J, Peterson B. Amygdala and hippocampus volumes in adolescents and adults with bipolar disorder. Archives of General Psychiatry. 2003;60:1201â1208. [PubMed] [GoogleScholar]

[58] Bradley M, Sabatinelli D, Lang P, Fitzsimmons JR, King W, Desai P. Activation of the visual cortex in motivated attention. Behavioral Neuroscience. 2003;117:369â 380. [PubMed] [GoogleScholar]

[59] Breslau N, Schultz L, Peterson E. Sex differences in depression: A role for preexisting anxiety. Psychiatry Research. 1995;58:1â 12. [PubMed] [GoogleScholar]

[60] Bradley M, Sabatinelli D, Lang P, Fitzsimmons JR, King W, Desai P. Activation of the visual cortex in motivated attention. Behavioral Neuroscience. 2003;117:369â 380. [PubMed] [GoogleScholar]

[61] Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161-1178. [Figure 2]. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2367156/figure/F1/.

[62] Posner, J., Russell, J. A., Peterson, B. S. (2005). The circumplex model of affect: an integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and Psychopathology, 17(3), 715-734. doi: 10.1017/S0954579405050340. PMCID: PMC2367156

[63] R. Picard, âAffective computing,â MIT Media Laboratory, Perceptual Computing Section, Tech. Rep. 321, November 1995.

[64] J. A. Russel, âA circumplex model of affect,â Journal of Personality and Social Psychology, vol. 39, pp. 1161â1178, 1980.

[65] K. Schaaff, âEnhancing mobile working memory training by using affective feedback,â in IADIS International Conference on Mobile Learning, 14-16 March 2013, Lisbon, Portugal, 2013.

[66] D. M. Diamond, A. M. Campbell, C. R. Park, J. Halonen, and P. R. Zoladz, âThe temporal dynamics model of emotional memory processing: a synthesis on the neurobiological basis of stress-induced amnesia, flashbulb and traumatic memories, and the yerkes-dodson law.â Neural Plasticity, vol. 2007, pp. 1â33, 2007.

[67] A. Lichtenstein, A. Oehme, S. Kupschick, and T. Ju Ìrgensohn, âCompar- ing two emotion models for deriving affective states from physiological data,â in Affect and Emotion in Human-Computer Interaction, C. Peter and R. Beale, Eds. Berlin, Heidelberg: Springer-Verlag, 2008, ch. Comparing Two Emotion Models for Deriving Affective States from Physiological Data, pp. 35â50.

[68] A. Haag, S. Goronzy, P. Schaich, and J. Williams, âEmotion recognition using bio-sensors: First steps towards an automatic system,â Lecture Notes in Computer Science, vol. 3068, pp. 33â48, 2004.

[69] S. K. DâMello, R. W. Picard, and A. C. Graesser, âTowards an affect- sensitive autotutor,â Special issue on Intelligent Educational Systems â IEEE Intelligent Systems, vol. 22, no. 4, pp. 53â61, 2007.

[70] B. Woolf, W. Burleson, I. Arroyo, T. Dragon, D. Cooper, and R. Picard, âAffect-aware tutors: recognising and responding to student affect,â Int. J. Learn. Technol., vol. 4, no. 3/4, pp. 129â164, Oct. 2009.

[71] G. N. Yannakakis and J. Hallam, âEntertainment modeling through physiology in physical play,â International Journal of Human-Computer Studies, vol. 66, no. 10, pp. 741 â 755, 2008.

[72] P. JercËic Ì, P. J. Astor, M. T. P. Adam, O. Hilborn, K. Schaaff, C. A. Lindley, C. Sennersten, and J. Eriksson, âA serious game using phys- iological interfaces for emotion regulation training in the context of financial decision-making,â ECIS 2012 Proceedings, vol. 20, 2012.

[73] Task Force of the European Society of Cardiology the North American Society of Pacing and Electrophysiology, âHeart rate variability : Standards of measurement, physiological interpretation, and clinical use,â Circulation, vol. 93, no. 5, pp. 1043â1065, 1996.