NeuroExplore - Visualizing Brain Patterns

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October 2017

Abstract

The objective of this project is the creation of a Physiological Computing Information Visualization (InfoVis) interface through which, interactively, users can visually decipher one's intricate emotions and complex mind-state.

To this end, we cooperated closely with Neuroscience experts from Instituto de Biofísica e Engenharia Biomédica (IBEB) throughout our work. Consequently, we assembled a Brain Computer Interface (BCI), from a Bitalino do-it-yourself hardware kit, for retrospective and real-time biosignals visualization alike. The resulting wearable biosensor was successfully deployed in an extensive database (DB) acquisition process, consisting of activities with concrete, studied brain-pattern correlations.

This big-data InfoVis foundation's magnitude and its, at times saturated, physical signal accredited the development of a data-processing pipeline. Indeed, our solution - entitled NeuroExplore - converts and presents this large number of digitalized, raw biosignal items into more recognizable visual idioms.

The system interaction was intentionally designed in order to augment users' discoveries and reasoning regarding visually recognizable metrics, as well as subsequently derived trends, outliers and other brain patters. Strengthening this intent, we adopted an iterative development process in which, recurrently, expert needs and user suggestions were equated as orienting guidelines.

This all culminated in a final version we deemed worthy of extensive functional and utility user testing and expert validation. In the end, our project achieved both excellent user usability scores as well as expert interest, some already relying on our solution for their own research.

Keywords: InfoVis, Physiological Computing, Affective Computing, Brain-Computer Interface, biosignals, qEEG

1. Introduction

Despite the advent of Computer Science, historically, Humanity has consistently relied on a more organic form of processing power: Our brain! This computer's intricate psycho-physiological inner workings seem ever elusive. Contemporaneously, the quest to study and better understand our mind and its processes is the purpose [11] of the interdisciplinary scientific field titled Cognitive Science. In this project, we are predominantly interested in two of its sub-disciplines: **Computer Science** and **Neuroscience** - the scientific study of the nervous system. Specifically, we are concerned with:

1. The relation between measurable user Physiological data, typically from the Central Nervous System (CNS), and specific brain behaviors, such as emotions. Neuroscientists have documented and correlated such relations typically via the usage of an Electroencephalogram (EEG) and its spectral analysis - Quantitative Electroencephalography (qEEG).
2. How to interactively, intuitively and graphically present an InfoVis which - visually - amplifies user cognition of the perception the subsequent, derived Psycho-Physiological data.

This insight is particularly useful for a diverse number of reasons, ranging from Health (epilepsy diagnose[2]), to Neuromarketing[17] and Entertainment[9]. Furthermore, contemporaneously, personal user information extremelly valuable for for Big Data User Behavior Analytics[19].

1.1. Objectives

The goal of this work is the development of an interactive visualization so that users better understand one's mental state and emotions via Psycho-Physiological input data.

Thus, a InfoVis assisted analysis, search and comparison of current and previous results could potentially identify new trends, outliers and features. In order to achieve our goal we must:

1. Research and choose a methodology to acquire a Physiological data collection for further

analysis.

2. Research and develop algorithms to derive Psycho-Physiological information from the original raw data

3. Develop an interactive visual interface to examine such data through the display of:

   (a) Real-Time Information

   (b) Retrospective Information

4. Validate our work through both user and expert feedback and its statistical analysis.

1.2. Contributions

Throughout our work, cooperation and mentorship from IBEB faculty members, actively participating as Neuroscience experts, is paramount to the understanding of Physiological Computing concepts, necessities and applications. In other words, IBEB contributions were indispensable in our journey to visually present the uncensored and inherently complex insight of our mental inner workings.

Correspondingly, IBEB colleagues showed interest utilizing our project. Specifically, our hardware and software implementation has been successfully used in hands-on demos, live data gathering, video pitches, Start-up accelerator events, scientific events and other projects.

2. Background

Due to the multidisciplinary nature of our work, we present a brief related IT fields of study background- within this context - whose concept's comprehension is of underlying interest for our project. Firstly, the field of **Sentiment Analysis**, also known as opinion mining, typically researches *term frequencies* and their *presence* in textual data input for psychological data extraction[10]. **Affective Computing** is concerned with the theory and construction of machines which can recognize, interpret and process human emotional states. It can encompass Sentiment Analysis and combine physiological data or - typically - facial video content analysis for feature distillation [15]. **Physiological Computing**, as implied, is interested in human physiological signal analysis, usually focusing on the nervous and cardiac system, but not exclusively [4]. Finally, **BCI** - aiming at improved Human Computer Interaction (HCI) - focuses on the brain's physiological output, typically via artificial intelligence based system that can recognize a certain set of patterns in brain EEG[8].

3. Related Work

Studying the best way to visualize and interact with our complex data can be help improve our project.

3.1. Textual Sentiment Analysis

Torkildson et al. [18] used machine learning AI techniques for sentiment analysis, emotion classification and corresponding visualization purposes. Specifically, emotional classifiers are defined and a 20 collaborative visualization is proposed after analyzing twitter posts' data preceding, during and after the 2010 Gulf Oil Spill Crisis.

Categorical Attributes of Emotion were defined based on Ekman's six basic emotions: joy, anger, fear, sadness, surprise and disgust. Sentiment attributes: negative, neutral and positive, were designated and intended to be mutually exclusive. Afterward, the purpose of the pretended visualization was set: "*support the analysis of the emotional impact of events*". Finally, the authors decided to graphically present the information using a stacked area chart. This idiom allows "*easy comparison of values, facilitated by the colored bands. The top 25% of values, the time instances with the highest emotion frequency, have the highest color saturation. The coloring makes these peaks easily distinguishable.*"

Ultimately, this paper provides an interactive VIS for emotional analysis which allows for tasks such as: "*What emotional response did the public manifest as a consequence of the POTUS speech?*" - to be accomplished

Kamvar and Harris [7] created an emotional search engine together with a web-based visualization. This was achieved extracting sentences from social media that include the words "*I feel*" or "*I am feeling*", as well as the corresponding author's sex, age, location and time of occurrence.

Combining these metrics allows for several distinct visualizations such as: bar-charts with age breakdown of feelings from people in the last few hours; world-maps characterized by a geographic breakdown of feelings from people in the last few hours; line-charts relating sentiments over time such as stress and relaxation over the week or love and loneliness in the week of Valentine's Day; stacked area charts relating a specific feeling's frequency over the aging of a human.

These results were based on an immense amount of different emotions or sentiments possible thanks to the applied text extraction technique. Combining these techniques with physiological input data could potentially yield even more accurate results. The overall result exposes the diverse capabilities of interfaces that allow for item-level exploration of sentiment data.

3.2. Video Content Affective Analysis

Hupont et al [6] created an emotional visualization – EMOTRACKER - employing not only facial analysis for emotion recognition purposes as well as

eye-tracking for gaze analysis.

After noting several industries' increasing desire for objective measurements of engagement with content, sparked by brands increasingly striving to build emotional connections with consumers, the authors note there is a lack of tools for achieving these aims. "*In fact, the important question of how to efficiently visualize the extracted effective information to make it useful for content designers has been scarcely studied*".

The resulting VIS was composed of two modes: "*emotional heat map*", with selectable emotional layers, and "*emotional saccade map*", with a dynamic representation that shows the path formed by the user fixation points (points the user had been looking at for a minimum configurable time, in milliseconds). In both modes, the users could also see their current emotional state via an emoticon as well as Eckman's six emotions, plus neutral.

Finally, it would be of scientific interest to analyze the impact in this VIS's accuracy if an EEG was added as input as done by Soleymani[16].

With millions of faces analyzed to date and one-third of the Global Fortune 100's companies using their technology, MIT's Media Lab's offspring Affectiva Inc has developed a video analysis emotion detection and visualization API – Affdex[1].

Arguing that Emotions are the number one influencer of attention perception, memory, human behavior and decision making, the API is capable of detecting Ekman's six emotions plus neutral, 15 nuanced facial expressions and even heart-rate by evaluating color changes in a person's face, which pulse each time the heart beats.

The resulting visualization consists of a retrospective line chart, generated after analyzing via webcam the user's reaction to an ad. This line chart compares different age groups reactions as well as the user's, along the ad's duration. The measured reactions are: Surprise; Smile; Concentration; Dislike; Valence; Attention; and Expressiveness. This demo is publicly available to test, online.

Emotient Inc. was a startup focused on video emotional analysis and its consequent visualization. Recently acquired by Apple Inc., the company's main product was an API called Emotient Analytics [2].

This software provided facial expression detection and frame-by-frame measurement of seven key emotions, as well as intention, engagement and positive or negative consumer sentiment. All of this was then incorporated in a visualization. In it we can see line charts for Emotional Engagement, Attention and Sentiment as well as the average of each of these metrics. Furthermore, stacked area chart displayed each emotion over time as well as pie charts for the video's average, emotional engagement and participants' gender.

The insight gained from quantifying emotions allowed companies to pinpoint and fix issues as well as improve their marketing performance. Additionally, all of this was accessible independently of platform, via a web browser

3.3. Physiological Computing

Gavrilescu and Ungureanu [5] investigated contemporary methods to display EEG data and subsequently proposed a new VIS. After mentioning the several useful usages of EEG, such as "*the assessment of a user's emotional state*", the authors note that the nature of EEG signals, lacking any intrinsic visual data, causes multiple challenges regarding their graphical representation. Particularly "for data spanning over frequency bands and extended durations". The current, most common ways, for EEG visual representation are then dissected: **Power Spectrum graphs** are identified as being time-consuming and tedious to compare . This issue is particularly severe when representing raw data for a large number of electrodes and for various brainwaves. **Volumetric bull's eye plot** - a 2D top-down disc-view of the cranium - is identified as an effective way of relating desired information for a single sample across all electrodes positions. However this idiom is unable to effectively represent complex, multivariate data concurrently. This is due to the difficulty to "*represent multi-value data across multiple ranges and time phases in a single image*".

Finally, a new VIS , aiming to "p*rovide an intuitive means of representing the data over multiple sample phases and for all available frequency bands*" is presented. Using color spots varying in size and color according to the brainwave frequency and voltage, respectively; and glyphs varying in volume depending on the variation of the data between consecutive time phases.

Cernea et al. [3] identified emotions with the purpose of enhancing the experience of multi-touch interfaces' users. A VIS is proposed for this context and this approach is verified conducting an EEG user study. The researcher's goal is to improve the user's emotional self-awareness; the awareness of other users emotion in collaborative and competitive scenarios; and the evaluation of touch systems and user experience through the visualization of emotions.

This was achieved using Russel's model[14] encoding a variety of emotions in terms of affective valence (pleasant or unpleasant) and arousal (excited or calm). Using EEG, facial expressions and

[1] http://www.affectiva.com/solutions/affdex/

[2] http://www.emotient.com/products

NeuroSky's MindWave is a BCI headset catering directly to the consumer market 8. The hardware consists three electrodes: a reference and ground electrodes located on a ear clip and one EEG electrode on the forehead above the eye (FP1 position)9.

MindWave's also supports previous recording data display in the format of an InfoVis . In it we can visualize brain-wave bands' intensities (counts) in a radar chart (left) as well as a colored bar chart (right). The raw EEG signal is displayed above the bar chart. Additionally, two circular meters display the normalized (1-100) Attention and Meditation metrics. This angular display of numbers is a bad practice as it complicates user comparison. An alternative, linear representation would fix this.

Finally, signal quality is also displayed so the user can better identify issues such as signal saturation.

Bitalino is a low-cost toolkit to learn and prototype applications using physiological signals10. It supports a wide range of sensors, although not all simultaneously, due to bandwith limitations [18]. Namely: an Accelerometer, photoplethysmography (PPG), Ecectrocardriography (ECG) and Electrodermal Activity (EDA/GSR). Additionally, a User Interface (UI) and VIS software - OpenSignals11 - can be installed for a real-time or retrospective analysis as well as loading of pre-recorded signals . On it we can see line charts displaying each sensor's signal.

OpenSignals main limitations are its lack of derived metrics, the VIS shows RAW data only; its absent of any post processing which can result in saturated signal visualization; its connectivity can be somewhat lacking and frequent crashes have been reported by IBEB faculty colleagues.

3.4. Discussion

It is clear that there are several distinct approaches and fields of research analyzing and scrutinizing one's mental state and emotions. Despite their accompanying User Interface (UI), a lacking amount of InfoVis specific Physiological Computing studies was, regrettably, registered With the exception of Gavrilescu's [5] work which sadly featured unjustified 3D interaction , we could not find any other EEG InfoVis.

Here lies our opportunity to expands the borders of scientific knowledge. Further motivating our work, we propose the development of an intractable and intuitive Psycho-Physiological visual medium. Through which, users will be able to better understand their emotional and mental inner-workings.

Figure 1: BrainBIT BCI final prototype used in this project.

4. Proposed Solution

This chapter portrays all the work which led into the most recent version of our proposed InfoVis solution.

4.1. Biosignals Input Solution

Efficient Neuro-Physiological acquisition is key for any biosignal database upon which we can develop and InfoVis, particularly so in real-time scenarios. This is comprehensible as the database itself is the foundation of any InfoVis. During initial IBEB meetings, we learned about the opportunity to use a novel HBI as input to a Physiological Computing InfoVis database.

Bitalino supports many distinct sensors, yet its analog ports are limited. See this and other features such as weight in Table. We equipped ours (Table.) with an accelerometer, four EEG electrodes and one PPG ear-clip sensor. The rationale behind this multi-sensor approach is straightforward. The accelerometer is used to detect user movement and the resultant signal saturation. Through EEG analysis, we can extract CNS information such as Emotional-Valence. The PPG allows us to estimate the user's heart rate and thus better understand his arousal levels. Technical specifications of the components can be found at Bitalino's website[3], including hardware datasheets[4]. The next step was the assemblage of the Bitalino. The pre-ordered Plugged Kit consists of electronics (cables, sensors, the processing unit and other blocks) but no supporting apparatus as seen in Figure . As such, a considerate amount of thought went into the ergonomics and the resistance to wear and transport of our device. Our solution, consists of two velcro strips glued to each-other with the hardware mostly between them.

The only visible electronic components on the inside of the strip are the electrodes. The PPG sensor, which hangs on the ear-side, the Power Block with its indicate LED and power switch and the battery are visible on the outer side of the strip. All of this is detailed and can be seen in Figure .

[3] http://bitalino.com/en/
[4] bitalino.com/datasheets

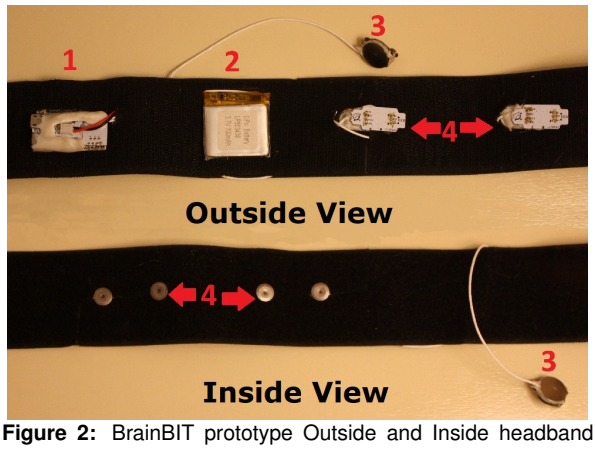

Figure 2: BrainBIT prototype Outside and Inside headband view detailing: (1) The Power Block; (2) Battery; (3) PPG; (4) Electrodes.

Finally, our headband had improved usability substantially over its original components. Its, wearable nature allowed it to be used without cables or any other support. Ergonomically, the soft component of velcro was placed in the inner side of the headband so that our prototype was comfortable and fitted users regardless head size.

This prototype's uniqueness entitled it its own name: BrainBIT. The final result can be seen in Figure.

4.2. Architecture

System architecture's can be divided in three main pillars: the hardware biosignal BCI; the users - whose perception we are attempting to improve; and the software - responsible filtering, processing and the derived data InfoVis.

The users' Physiological (EEG and PPG) and Physical (accelerometer) input is read by BrainBIT, which in turn, listens for requests - sent over Bluetooth by ClientBIT (a front-end Javscript/HTML). A raw, discrete domain, digitalized version of the user's biosignals is then sent to ClientBIT which forwards it to ServerBIT (Python back-end) for post-processing. Communication abides JSON-formatted, preprocessed data. The user interacts with the InfoVis via coordinate input, typically a mouse, as he watches current or previously recorded datasets.

4.3. Development Process

With our hardware means of raw, biosignal data acquisition established, we now present all stages of development which led into our final, interactive InfoVis solution: NeuroExplore.

Biosignals Dataset Development: The foundation for any InfoVis system is the data whose cognition, perception and insight we are attempting to revolutionize. That is, to transform and represent data in a form that allows human interaction such as exploration and newfound knowledge as a result. This is what differentiates an InfoVis from a more traditional and elementary Graphical User Interface.

Figure 3: Physiological Computing Database Acquisition featuring early InfoVis prototype.

As such, we devised a set of four tasks: Meditation, Puzzle-solving, music-listening and video-watching during which three subjects wore BrainBIT. This data-base building processes included twenty different sessions (each comprising four tasks) for each user. After this process ended, we counted 250 Comma Separated Value files comprising 7.97 Gigabytes. Given the nature of biosignals (susceptible to saturation) we then decided to filter our data.

Data Preprocessing: The voluminous nature of collected, enigmatic, raw biosensor data added to its susceptibility to realtime recording condition deterioration demanded preprocessing, for feature extraction and filtering purposes. As such, we started by building a data cleaner Python script, which we used for the retrospective database and extended it into the real-time back-end preprocessing development. NeuroExplore data preprocessing is implemented by the Python server - serverBIT. Receiving as input the unprocessed biosensor signal, this back-end component is tasked with the following successive data transformations:(1) Filtering Signal Saturation; (2) Calculating the EEG Power Spectrum; (3) PPG blood volume pressure Peak-Finding.

Derived Data: NeuroExplore relies on attributes derived from the ServerBIT output of preprocessed data. The front-end (ClientBIT) derived each of the following metrics: Theta, Alpha and Beta brain oscillations; Heart-rate; Emotional Valence; Engagement; and Meditation. These last three metrics in particular: Emotional-Valence, Engagement and Meditation, are determined exclusively for each second of non-saturated communication. This was intended as it is futile to derivate metrics from a saturated signal. In these missing value situations, we opted to assign the previously, adequately derived, metric.

InfoVis Development: Iterative development process stages led into the current version of NeuroExplore, a Physiological Computing InfoVis through which users can betterdecipher their brain and body's Psycho-Physiological state. Neu-

roExplore handled specific data structures to achieve a fast action/feedback loop required by dynamic queries, through vision and biosignals alike. These components are integrated into a coherent framework that simplifies the management of sophisticated physiological data structures through the BrainBIT BCI or our collected database, the Server-Bit Python back-end, and the InfoVis Javascript implementation, ClientBIT.

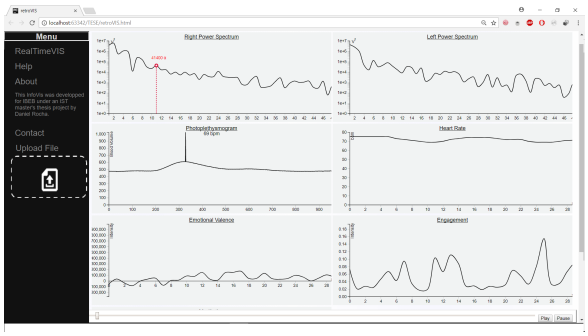

Figure 4: NeuroExplore InfoVis final-version screenshot

4.4. Discussion

Throughout this section, we have detailed the iterative development process which led into the final, most current implementation of NeuroExplore.

Through the development of this Physiological Computing InfoVis - intended to improve the user's ability to decipher their mental state - we reached several veredicts:

1. We acquired and preprocessed a massive (5,81GB) biosignals database, featuring approximately 18 hours of recording spanning 250 CSV files divided into three subjects and four categories associated with specific, measurable and studied mental patterns.

2. BrainBIT Physiological Computing database acquisition capabilities have been proven. It presented outside electromagnetic noise susceptibility - visible in NeuroExplore - which needs to be managed. Additionally, the PPG sensor signal outputted weak signals in some users. We believe this is related to lightning conditions, which, if correctly handled, work as intended.

3. Our Bitalino sensor specs feature three channels which - thoughtfully - could reassigned. The accelerometer's anticipated filtering enabling insight proved fruitless, as EEG signal saturation filtering encompassed it. Currently, we have no use for this output, but have decided to keep it as part of our project to avoid risking future developments.

4. There is extended neuroscientific research regarding EEG derivation of psychophysiological metrics. We have meticulously detailed our proposed extraction algorithms - and justified them accordingly.

5. A final version of NeroExplore is proposed, and its features are widely dissected: from the initial data's output, through preprocessing, back-end, mechanisms and data derivation alike, to the front-end interactive visual display.

Through the iterative development of project, user - and often expert - feedback was equated and incremented into each surpassing version, thus increasing our goal's success prospects by repeatedly reality-checking countless preconceived notions

In sum, NeuroExplores current prototype varied features warrant it the right to be tested with a larger pool of users and throughly validated, via usability and utility testing alike.

5. Evaluation

Validating an InfoVis is an indispensable external indication of its features successful implementation. We will assess its usability and functionality by testing if our design has succeeded in its purpose[12].

In order to validate our solution, we decided to tackle this challenge in two distinct approaches: Usability Testing and Case Studies. The former was undertook by users without previous knowledge of the system. This was intentional in order to evaluate the system in regards to interactivity and usability. Testers were asked to complete a set of tasks and a quiz while under observation. After which, a discussion where overall feedback and personal suggestion took place. The latter corresponds to two experts in biomedicine engineering interacting with the InfoVis while providing functional feedback.

5.1. Usability Tests

Upon many iterations of development, a final version of our VIS must be subjected to a summative evaluation. This is intended to determine our prototype's usability success as well as assuring a mean of maintaining standards [13]

In this section we will detail how the user testing was conducted, depicting each user task and its derived, quantitative data: the amount of time necessary for the user to successfully complete each task; and the number of errors made. Additionally, upon task completion but before feedback took place, participants are asked to fill a SUS, "a highly robust and versatile tool for usability

professional"[1]. Consequently, we could establish a concrete, comparable $[0-100]$ usability score.

Results: Users successfully (never averaging more than 0,5 errors per task) completed the tasks we posed them. On average, Identify and Compare tasks took longer $[14,14-14,41]seconds$ sthan mere Discovery tasks $[8,05-8,55]seconds$, as expected. Finally, users scored our solution as excellent - according to SUS collected results.

Figure 5: System Validation: On the bottom-right we can see a participant filling the SUS

5.2. Case Studies

Two experts participated in the case studies ascribing the think-aloud protocol while exploring our system.

Results:Both participants extensively and enthusiastically transversed our system's functionalities with ease. Through NeuroExplore, they could visualize raw physiological data as well as the derived affective and nervous-system related metrics both in real time as well as retrospectively. As pointed out, this contrasted with their current solution which relied on OpenSignals VIS's restriction to raw values (see figure 3.31 for reference).

Overall, comments were extremely positive. The purposefully minimalistic and sober menu UI, as well as its smooth animation and clean color pallet were praised. Participants appreciated these aesthetics in what they deemed as corresponding to the simple and intuitive user-system interactions. In detail, line-chart mouse interaction resulting in data knowledge without the visual aid of the scales was exalted. What's more, the location of the remaining interactions inside an extendable menu was pointed out as facilitating both the analysis of a wider area of visible data as well as overall interaction with other relevant system functions by concentrating all these in one place.

Interestingly, the employed algorithms and their respective representation were discussed as well as the on-field data collection possibilities of our projects' web-based nature.

Additionally, testers stressed recurring connection issues while recording data using OpenSignals. These situations could potentially frustrate user recording sessions. Thus our positive experience when using our solution to collect data was appreciated and successfully put to the test.

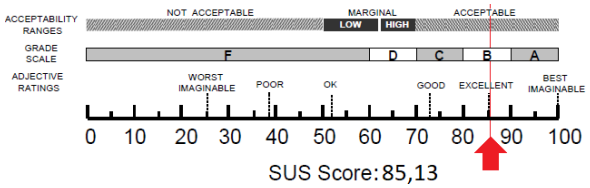

Figure 6: Final SUS Score

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tion alike, to the front-end interactive visual display.

Through the iterative development of project, user - and often expert - feedback was equated and incremented into each surpassing version, thus increasing our goal's success prospects by repeatedly reality-checking countless preconceived notions

In sum, NeuroExplores current prototype varied features warrant it the right to be tested with a larger pool of users and throughly validated, via usability and utility testing alike.

6. Conclusion

In retrospective fashion, this thesis begins with the introduction of our project and the postulus of comprising objectives which lead into the implementation of NeuroExplore. Given the diversified fields of study our solution transverses, we presented a diversified pallet of background knowledge: this ranged from the more traditional, text derived field of Sentiment Analysis, passed through Affective Computing and its increment on this method via multi-modal approaches, to arrive at the complementary fields of Physiological Computing and - in particular - BCI. This Computer Science meets NeuroScience backdrop then into a related work, InfoVis examples of both proprietary and academical nature. The document progresses by comprehensively entailing development process leading into our final implementation, namely: the software and hardware's architecture, the database acquisition process and its preprocessing, the derived metrics rational and protocol, and - finally - the iterative development nature and its procedural growth. Lastly, we vindicate NeuroExplore through a comprehensive functionality and usability, user and expert validation.

NeuroExplore is a Physiological Computing InfoVis prototype, through which users can better comprehend one's current or previously recorded brain and body status. Achieving a SUS of 85:13, the system was considered excellent by users and experts alike. Coherently, we have fulfilled our main project goal (see Chapter 1) and all of its dependencies, namely, a data pipeline which seemingly converts imperceptible biosignals into an insightful AbstractVIS, for increased, mind and body, behavior insights.

References

[1] J. Brooke et al. Sus-a quick and dirty usability scale. *Usability evaluation in industry*, 189(194):4–7, 1996.

[2] A. J. Casson, D. C. Yates, S. J. Smith, J. S. Duncan, and E. Rodriguez-Villegas. Wearable electroencephalography. *IEEE engineering in medicine and biology magazine*, 29(3):44–56, 2010.

[3] D. Cernea, C. Weber, A. Ebert, and A. Kerren. Emotion-prints: interaction-driven emotion visualization on multi-touch interfaces. In *Visualization and Data Analysis*, page 93970A, 2015.

[4] S. H. Fairclough. Fundamentals of physiological computing. *Interacting with computers*, 21(1-2):133–145, 2008.

[5] M. Gavrilescu and F. Ungureanu. Enhanced three-dimensional visualization of eeg signals. In *E-Health and Bioengineering Conference (EHB), 2015*, pages 1–4. IEEE, 2015.

[6] I. Hupont, S. Baldassarri, E. Cerezo, and R. Del-Hoyo. Advanced human affect visualization. In *Systems, Man, and Cybernetics (SMC), 2013 IEEE International Conference on*, pages 2700–2705. IEEE, 2013.

[7] S. D. Kamvar and J. Harris. We feel fine and searching the emotional web. In *Proceedings of the fourth ACM international conference on Web search and data mining*, pages 117–126. ACM, 2011.

[8] M. B. Khalid, N. I. Rao, I. Rizwan-i Haque, S. Munir, and F. Tahir. Towards a brain computer interface using wavelet transform with averaged and time segmented adapted wavelets. In *Computer, Control and Communication, 2009. IC4 2009. 2nd International Conference on*, pages 1–4. IEEE, 2009.

[9] L.-D. Liao, C.-Y. Chen, I.-J. Wang, S.-F. Chen, S.-Y. Li, B.-W. Chen, J.-Y. Chang, and C.-T. Lin. Gaming control using a wearable and wireless eeg-based brain-computer interface device with novel dry foam-based sensors. *Journal of neuroengineering and rehabilitation*, 9(1):5, 2012.

[10] W. Medhat, A. Hassan, and H. Korashy. Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, 5(4):1093–1113, 2014.

[11] G. A. Miller. The cognitive revolution: a historical perspective. *Trends in cognitive sciences*, 7(3):141–144, 2003.

[12] T. Munzner. *Visualization analysis and design*. CRC press, 2014.

[13] Y. Rogers, H. Sharp, and J. Preece. *Interaction design: beyond human-computer interaction*. John Wiley & Sons, 2011.

[14] J. A. Russell. Core affect and the psychological construction of emotion. *Psychological review*, 110(1):145, 2003.

[15] K. R. Scherer, T. Bänziger, and E. Roesch. *A Blueprint for Affective Computing: A sourcebook and manual*. Oxford University Press, 2010.

[16] M. Soleymani, S. Asghari-Esfeden, Y. Fu, and M. Pantic. Analysis of eeg signals and facial expressions for continuous emotion detection. *IEEE Transactions on Affective Computing*, 7(1):17–28, 2016.

[17] S. J. Stanton, W. Sinnott-Armstrong, and S. A. Huettel. Neuromarketing: Ethical implications of its use and potential misuse. *Journal of Business Ethics*, 144(4):799–811, 2017.

[18] M. K. Torkildson, K. Starbird, and C. Aragon. Analysis and visualization of sentiment and emotion on crisis tweets. In *International Conference on Cooperative Design, Visualization and Engineering*, pages 64–67. Springer, 2014.

[19] P. Zikopoulos, C. Eaton, et al. *Understanding big data: Analytics for enterprise class hadoop and streaming data*. McGraw-Hill Osborne Media, 2011.