OutOfColor

by

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Introduction:

Color is a central part of people's experience of the world. Entire fields of research ranging from neuroscience, psychology, philosophy, art, and design have been dedicated to understanding the mechanisms of color perception. Advertising, design, entertainment, and media rely on color as a primary tool to direct attention and influence behavior. Yet describing what color is and the mechanisms by which color perception works is a no easy task. To the average sighted person, colors would seem to be objective parts of or represent the state of things in the physical world. Yet each of these assumptions is fundamentally wrong. Ultimately, in the absence of an observer, color, as with any other sensory quality, does not exist. Perceptual color qualities (hue, saturation, lightness/brightness, etc.) do not in any simple way correspond to the physical characteristics of retinal stimuli. That is to say, colors are not properties of objects or conditions of the world but are instead subjective qualities generated by the brain for the beneficial advantages they confer (Purves & Lotto, 2011, p. 53). Despite color being a quality that many know but none fully understand, the significant role it plays in determining moods, directing attention, and influencing behavior makes it nonetheless a phenomenon worthy of further interest.

The project described in this paper draws on past research to develop a generative interface system that immerses the user in a biofeedback loop dynamically linking color perception to the user's emotional states. He/she experiences color under novel conditions, prompting self-reflection on the mechanisms by which he/she is seeing. Under these conditions, the user's perception is cast in hues, contrasts, and intensities dictated by his/her emotions while his/her emotions are simultaneously affected by the perceptual qualities of the images as they are presented. In doing so, this project introduces a potentially new way to consider, explore, and experience the relationship between color and emotion.

This thesis is organized as follows: First, I offer a brief summary of the research surrounding the relationship between color and emotion, as well as the findings and methodologies of related studies, including some of those partially adopted in the design of this interface system. I focus on studies that take advantage of recent developments in brain sensing technologies. Particularly important are those investigating the application of electroencephalograph (EEG) signals in their attempts to systematically classify emotional states from neural oscillations (popularly referred to as “brain waves”). EEG signals refer to cortical electrical activity of the brain recorded by electrodes placed on the scalp. Emotional classification from EEG signals involves extracting emotion-related features (primarily *arousal* and *valence* levels, which I will define later) from EEG signals to characterize states of emotion within an emotion model. This paper describes the methodologies used to inform the generative design of this interface system, which relies on extracting *arousal* and *valence* features from EEG signals using the commercially available MUSE brain sensing headband. I then outline my approach to designing a system which feeds this neural information back to the user in the form of a modified visual field. Specifically, the color properties of hue, saturation, and lightness/brightness are dynamically adjusted according to changes detected in the user’s emotional state as mapped on a 2D matrix. This thesis concludes with a discussion of some of the methodological implications and limitations of this project. The potential of projects that seek to experiment with, explore, and engage with color in the novel ways this system enables are considered and directions for future research are proposed.

Background:

Color possesses a unique ability to imbue objects, artworks, or experiences with emotional and psychological meaning, direct attention, and influence behavior in a diverse range of settings. However, the relationship between color and emotion is a complex one. Understanding color's power to influence affective states has long been a contentious point of study and exploration.

The affective power of color is revealed through the strong influence it has been shown to possess in determining brand recognition, customer attitudes, directing attention, affecting customer behaviors, and driving purchasing decisions in a consumer setting. Color is leveraged as a primary tool in marketing, advertising, and design. In his review of literature related to color psychology, Satyendra Singh highlights the importance of color in marketing, asserting that "about 62-90 percent of the assessment that goes into people's decisions when interacting with people or products is based on colors alone" (Singh, 2006, p. 784). Singh holds that managers can use colors to increase or decrease appetite, enhance mood, calm customers down, and, reduce perception of waiting time. He further affirms that "prudent use of colors can contribute not only to differentiating products from competitors, but also to influencing moods and feelings - positively or negatively - and therefore, attitude towards certain products" (Singh, 2006, p. 786).

Research pointing to the powerful influence of color in branding provides further evidence of the importance of color in a consumer setting. In a retail setting, the use of strategic colors in store design can direct customers' attention. People can be drawn to the colors of walls, window displays, and store interiors that might influence their brand perception and buying behaviors (Bellizzi et al., 1983). Some studies even suggest certain kinds of colors can be correlated with different buying behaviors (i.e. spontaneous/unplanned purchases vs. planned/contemplated purchases) (Bellizzi et al., 1983). For its central role in logo design and packaging, color is a highly-regarded tool for building brand meaning. Consumers' preferences for and experiences of products have been shown to be largely shaped by package colors. One behavioral study establishes that different colors can attract the involuntary and voluntary attention of consumers (Kauppinen-Räisänen et al., 2010). In certain contexts, some create an attractive aesthetic experience while others communicate information relevant for the task at hand (Kauppinen-Räisänen et al., 2010).

The colors used in a company or brand's logo can also bring inherent and immediate value for consumers that can help a brand properly position itself. Bottomley and Doyle define the "appropriateness" of the colors used in a brand's logo by the congruity between functional products (solving/preventing problems) and functional colors (i.e. black, grey, green, blue) and sensory-social products (fulfilling needs for sensory pleasure and stimulation) and sensory-social colors (i.e. red, yellow, pink, purple) (Bottomley et al., 2006). Recently, augmented by the addition of digital technologies, color maps of logos within a particular industry are increasingly used by companies and brands during initial situation analysis to inform the design of new logos (O'Connor, 2010). Such processes involve applying systematic approaches to identify and document the range and nature of color characteristics within a given environment (O'Connor, 2010, p. 57). The result of the color mapping process is a database that provides a means of identifying patterns of similarity or dissimilarity as well as opportunities for differentiation using color ((O'Connor, 2010, p. 57-58). Highly systematic methods, like color mapping, aimed at effectively leveraging color in design highlight color as a highly regarded tool for companies to consider to achieve differentiation in a competitive environment.

The role of color in marketing and branding illustrates the perceived relationship between color and emotion. However, as pointed out by Whitfield & Whitshire, while “the assumption that colors are perceived as possessing emotional and mood characteristics has received experimental support,” it is also the case that “the evidence linking preference or reactivity to color with specific emotional or personality traits remains totally inconclusive” (Whitfield & Wiltshire, 1990, p. 387). Color preferences have been shown to vary considerably with age, gender, and culture according to some studies and not much according to others, and still the preferences of any individual might differ from another within the same group (Whitfield & Wiltshire, 1990, p. 387). Some research concludes that color preference and connotation is subject to great individual and group differences and is highly sensitive to contextual change while Other sources assert that despite its variability, a universal order of color preference does exist and certain colors bear inherent meanings and affective influences across these differences (Barton, Hill, & Widermann, 2014; Hupka, 1997; Whitfield & Wiltshire, 1990). In summary, despite its being a well-researched area including over a century of experimental work, measuring the descriptive and evaluative responses to color has proven to be a subtle and complicated undertaking. As I describe in the following section, the lack of consensus on this topic is largely rooted in a fundamental flaw underlying the approach of traditional studies. The novel approach introduced in this project is relevant in that it could offer a step to avoid these flaws and potentially overcome some of the challenges to better understand the relationship between color and emotion.

The Inverse Problem of Emotional State Classification

Several studies have produced frameworks that aspire to codify the relationship between emotion and color perception. However, the lack of agreement on the affective qualities of colors and the overall correlation between color and emotion presents an "inverse problem" that prevents accurate codification of this complex relationship. An inverse problem refers to the process of calculating from a set of observations the causal factors that produced them (Argoul, 2012, p. 1-5). In the case of color and emotion, codifying the relationship between the two phenomena rests on the ability to classify emotional states by some systematic process. Many studies have proposed systems to accurately classify emotional states as we experience them. Several models, based on varying theories and dimensions of emotion, have been established to provide an adequate classification space for emotion, the most prominently accepted being the Circumplex Model, the Vector Model, and the Positive Activation – Negative Activation (PANA) model (Rubin et al., 2009).

In contrast to the Circumplex model, which holds that emotions are distributed in space with dimensions of arousal and valence in a "circular, or donut, pattern centered on medium arousal and neutral valence", the Vector model holds that there is an "underlying dimension of arousal and a binary choice of valence that determines direction" (Rubin et al., 2009, p. 1). The result of this model is "two vectors that both start at zero arousal and neutral valence and extend as straight lines, one in a positive, and one in a negative valence direction" (Rubin et al., 2009, p. 1-2). The PANA model is commonly understood as a "45-degree rotation of the Circumplex model, defined by two primary axes reflecting two basic behavioral systems": Positive Activation (PA) (anchored at one end by mood terms like active, elated, and excited and at the other by drowsy, dull, and sluggish) and Negative Activation (NA) (anchored by distressed, fearful, nervous and by calm, at rest, and relaxed) (Rubin et al., 2009, p. 2-3). The Vector model and the PANA model are similar in that they are defined by their extremes whereas the Circumplex is defined by a central state of medium arousal and neutral valence. In the context of EEG-based emotion detection, any of these dimensional models suggest affective states as arising from a common, neurophysiological system. However, they differ in the ways they propose emotional features can be interpreted to define basic emotional states.

The main issue facing virtually every proposed framework for emotion classification is a lack of any quintessential definition of emotion itself as a concept or state of being. So, in the context of the inverse problem, which starts with the results and calculates the causes, the results of the phenomenon to be measured are unclear when it comes to emotional state classification. In other words, the processes developed thus far are flawed from the start.

As pointed out by Klaus R. Scherer on the topic of measuring emotions, “without consensual conceptualization and operationalization...progress in theory and research is difficult to achieve and fruitless debates are likely to proliferate” (Scherer, 2005, p. 695). Attempts to classify emotional states carry the risk of grouping fundamentally different affective processes, states, or traits under one term of “emotion”. With no consensus amongst studies on the specific neurophysiological systems from which they propose emotions arise, precisely what each of these studies actually defines comes into question. It would be reasonable to consider the possibility that in their attempts to classify emotional states, each of these studies could instead be characterizing different responsive states (i.e. the impulse to engage or avoid, react or reflect) or different parts of a more complex system that gives rise to the perceptual phenomenon of “emotion”. This lack of conceptual understanding related to emotion and the risks it has shown to pose are carefully considered in the designing of this generative interface system. The deliberate efforts made in this project to avoid falling victim to these risks and how such challenges should be considered moving forward are discussed later in this paper.

Circumplex Model of Emotion

This project adopts a version of the Circumplex model of emotion (Figure 1) developed by James Russell to interpret emotional states as combinations of two levels: arousal (how excited or relaxed one is) and valence (overall negative or positive state of mind) (James, 1980; Posner, 2005). Past studies that have proposed systems for EEG-based emotion classification have successfully applied versions of the Circumplex model (Ramirez et al., 2012).

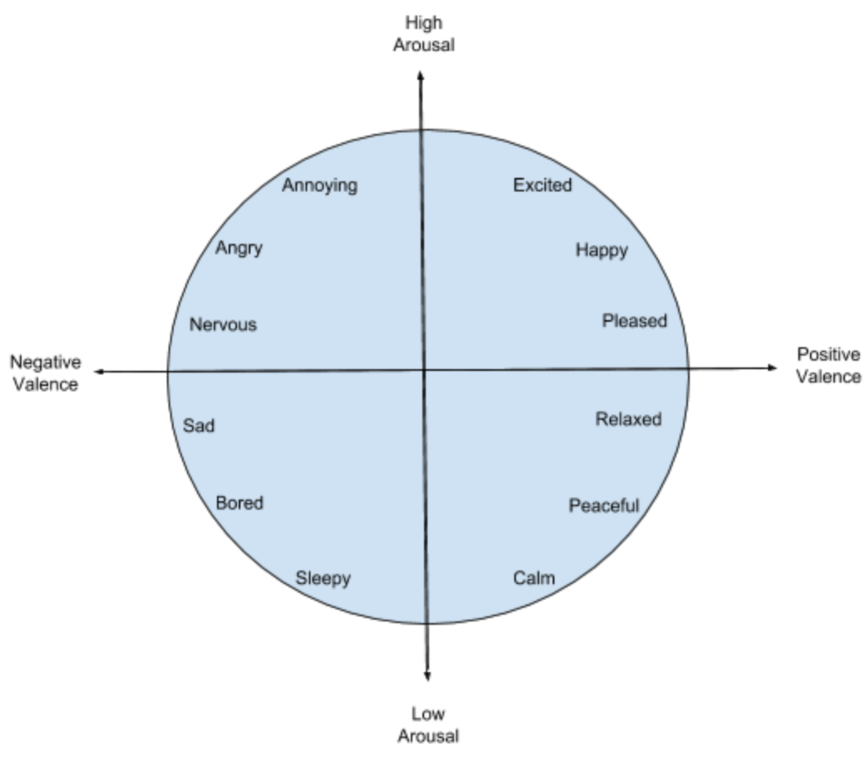

Figure 1: *Circumplex model as used in Ramirez et al., 2012*

Ramirez et al. 2012, describes a machine learning approach to detect emotion from EEG-based brain activity. In their study, they present subjects "auditory stimuli from a library of emotionannotated sounds and record their response EEG activity". The EEG signals are then filtered and processed in order to "extract emotion-related features". Machine learning techniques are applied in this study to "classify emotional states into high/low arousal and positive/negative valence" (e.g. happiness is a state with high arousal and positive valence, whereas sadness is a state with low arousal and negative valence) (Ramirez et al., 2012).

Studies such as Ramirez et al. 2012 demonstrate how the Circumplex model should be considered for its application in this project. The Circumplex model distributes emotional states on a two-dimensional circular space determined by arousal and valence levels. The vertical axis represents arousal, the horizontal axis represents valence, while the center of the arousal-valence space (AVS) represents a neutral valence and a medium level of arousal. As illustrated in the Ramirez et al. study and presented in Figure 1, the Circumplex model's classification of emotions as states of arousal and valence therefore relies on systematically establishing a "central" state of medium arousal and neutral valence around which all other emotional states are defined.

The Circumplex model is adopted for this project partially due to its successful application in related studies such as Ramirez et al. 2012, which has informed much of the methodology for this project (Posner, 2005). Furthermore, this project seeks to establish an interface system that detects the user's emotional state at the time in which they are immersed and visualizes emotional changes about that central state. As per the description of the three models presented above, the Circumplex model seems to be most aligned with this design and therefore the most appropriate model to adopt for this project.

Detecting Emotion from EEG Signals

Wang et al. identify three major approaches to emotion recognition that have been developed over the past few decades. Audio-visual analysis focuses on facial expression or speech and allow noncontact detection of emotion; however, these techniques are prone to deception due to the variability of these parameters (Wang et al., p.94). A second approach monitors changes in peripheral physiological signals (i.e. electrocardiogram (ECG), skin conductance (SC), respiration, and pulse) in response to different emotional states. Such methods provide more detailed, complex information for estimating emotional states (Wang et al., p.94). Finally, the third major approach focuses on brain signals (i.e. electrocorticography (ECoG), functional magnetic resonance imaging (fMRI), and electroencephalograph (EEG) (Wang et al., p.94-95). As a result of recent technological advances in dry electrodes, digital signal processing, and machine learning, as well as the increasing affordability of modern EEG devices, the use of electroencephalograms (EEGs) to detect emotion has become more accessible. Studies such as those that determine color preference or that detect and classify emotional states from EEG signals have proven electroencephalogram (EEGs) analysis highly capable of revealing features that characterize emotional states (Kawasaki & Yamaguchi, 2012; Ramirez & Vamvakousis, 2012; Choppin, 2000; Wang et al.).

In this project, the MUSE brain sensing headband is the device used to detect brain wave responses from electroencephalogram (EEG) signals. The MUSE EEG technology was selected due to its being relatively affordable and accessible and its proven ability to provide robust, real-time insight into brain activities by leveraging "advances in dry sensor technology" and digital signal processing ("Our Research"). The MUSE brain sensing headband, which retails in April 2018 for $249.00 USD, has a lightweight, flexible, adjustable design and features wireless

Bluetooth streaming capabilities. The goal of this project is to develop an interface system that is accessible and engaging for the average person. For this reason, the MUSE brain sensing headband is well suited to create an ideal user experience. Furthermore, the MUSE headband's design includes two channels located on the prefrontal cortex regions (one on the left and one on the right) and two on the temporal regions (one on the left and one on the right) (Figure 2). This allows for exploration of hemispheric asymmetries in the brain. For their suggested indication of motivational direction, which is generally related to affective valence, hemispheric differences are a critical feature to this system's algorithm for classifying emotional states from EEG responses (Davidson et al. 1990; Ramirez et al., p.179; Harmon-Jones, p.840).

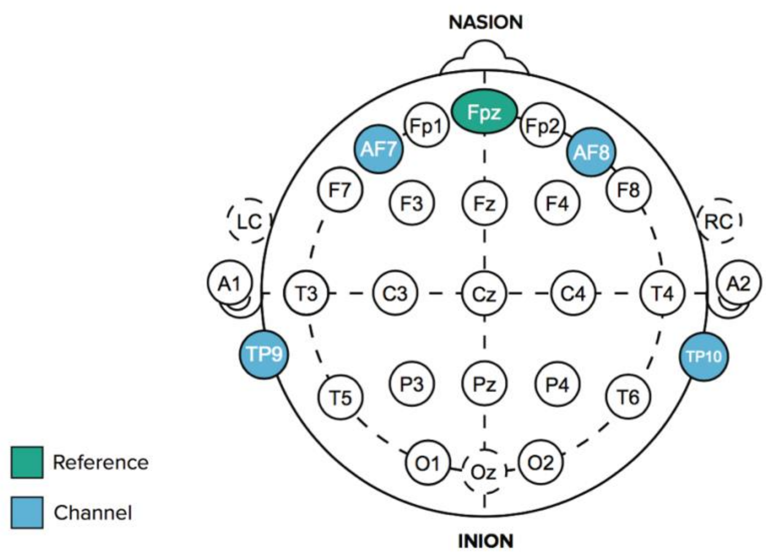

Figure 3: *Muse electrode locations* (Hardware Specifications)

Adapted Approach

This generative system highlights the unique opportunities to apply electroencephalography (EEG) technologies in novel ways. The goal of this project is to create an interface system that engages the user more closely with color as it relates to emotion. In doing so, this project also seeks to introduce and assess a new methodological framework for future studies to examine this relationship. The presentation of this system prototype in the form of an interactive web-page that can be easily run on a tablet or smartphone provides users an engaging way to explore concepts related to color. The generative system immerses users in a biofeedback loop (Figure 3) by adjusting the color qualities of a live video feed from a tablet or smartphone's camera according to changes in the user's emotional features. Brain wave activity data, extrapolated from EEG signals, is streamed to the user's device from the MUSE headband via Bluetooth. This data is filtered and processed to extract the emotion-related features and locate a point on the AVS plane. Each point on the AVS plane maps to a unique color effect determined by the hue, saturation, and lightness/brightness levels (Figure 4).

In this way, the system dynamically elicits unique color responses as changes in the user's classified emotional state occur in essentially real time. With this design, the system seeks to avoid the issue confronted in traditional attempts to classify emotional states. By mapping emotion-related features to perceptual consequences for the user to experience rather than to predefined classifications or labels of emotional states, the system does not rely on having a predefined definition of emotion. Instead, when viewing the world in this way, the user is immersed in a state where colors become entirely negotiable and his/her emotional state is presented as simultaneously determining and being determined by color perception.

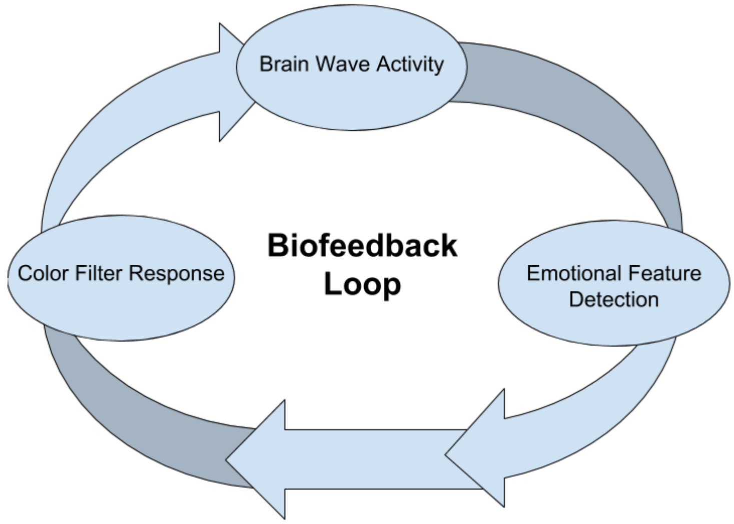

Figure 3: *Overview of biofeedback loop generated by system*

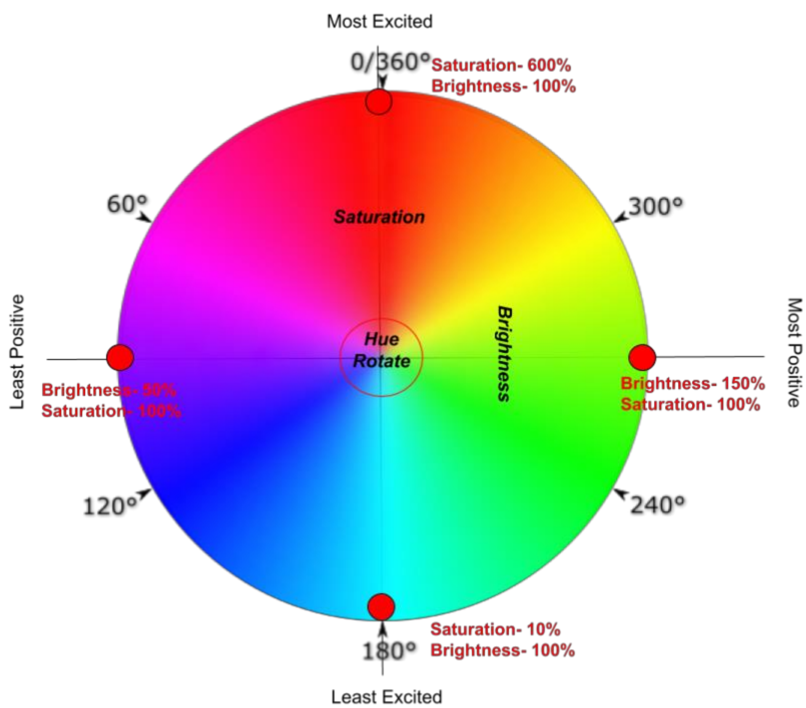

Figure 4: *AVS plane demonstrating process for mapping emotion-related features to color-consequences*

Methodology:

Emotional Feature Detection

Methods for emotional feature detection in this project are partially adopted from a study conducted by Ramirez and Vamvakousis (2012). Their study detected emotional features of arousal and valence from EEG signals using the Emotive Epoc Device (another wearable EEG technology) and applied machine learning approaches to classify them into emotional states within an arousal-valence 2D emotion model. Studies indicate that beta waves (13-30Hz) are primarily associated with states of alertness or excitement and alpha waves (7.5-13Hz) are primarily associated with states of relaxation, restfulness, and even brain inactivation (Davidson et al., 1979, p.202). Thus, this system developed in this project determines arousal by calculating the ratio of the absolute beta wave signal and the absolute alpha wave signal, each of which is the average of the signals recorded at all four channels (TP9, AF7, AF8, TP10).

Furthermore, research points to the differences in activation between the cortical hemispheres of the brain as indicative of motivational direction (approach or withdrawal behavior towards/away from a stimulus) (Davidson et al. 1990, p.330-331). However, as Ramirez & Vamvakousis (2012) point out, affective valence is related to motivational direction. Therefore, to determine valence, it is reasonable to compare hemispherical activation (Ramirez & Vamvakousis, 2012, p.179). With left frontal inactivation suggested to indicate negative emotion and right frontal inactivation suggested to indicate positive emotion, the user's valence level is determined by computing the difference between the alpha/beta power ratio in the left front channel (AF7) of the MUSE headband to the alpha/beta power ratio in the right front channel (AF8) of the MUSE headband:

Arousal = betaAVERAGE/alphaAVERAGE

Valence = alphaRIGHT/betaRIGHT − alphaLEFT/betaLEFT

Together, these two features are used to interpret brain wave response data from the MUSE headband as locations in a 2-dimensional representation of human emotional space, mapped as a point on the AVS plane.

Technical Overview

The system I describe here relies on processing, streaming, and transforming brain wave activity data from the MUSE brain sensing headband in a way that it can be visualized on the user's device. For the sake of leveraging resources currently available and turning out a prototype in a timely manner, this system makes use of the MUSE Monitor mobile application for its signal processing and streaming capabilities. Two more important tools used to complete this prototype include Node.js (https://nodejs.org)- an open source server framework used to deliver real-time data to the web-application, and p5.js (https://p5js.org)- a JavaScript library that enables a full set of drawing functionalities in the browser. P5.js was used in this project to capture and write live video frames to the user's screen and to dynamically apply color-related filters (Heller, Igoe, https://p5js.org).

An overview of the general steps by which this system works to obtain, process, transform, and ultimately visualize brain wave data from the MUSE headband (Figure 5) can be described as follows: The user connects the MUSE headband to a mobile device via Bluetooth and runs the MUSE Monitor application. From the MUSE Monitor app, live brain wave activity data is delivered to the user's tablet or smartphone. Live OSC data on the user's brain wave activity is streamed from the MUSE Monitor mobile app to a Node.js server which, through a Websocket client connection, delivers the data to the front-end web-application being run in the browser (West, n.d.). At this point, calculations are performed to detect emotion-related features and the color-related filters that are defined as functions of such. The p5.js library is used to capture video frames from the device's onboard camera. The video capture system then writes video frames to the browser screen of the user's device and color-related filters are dynamically applied to the canvas at each frame. The color filters are dynamically modified according to the brain wave data received by the application.

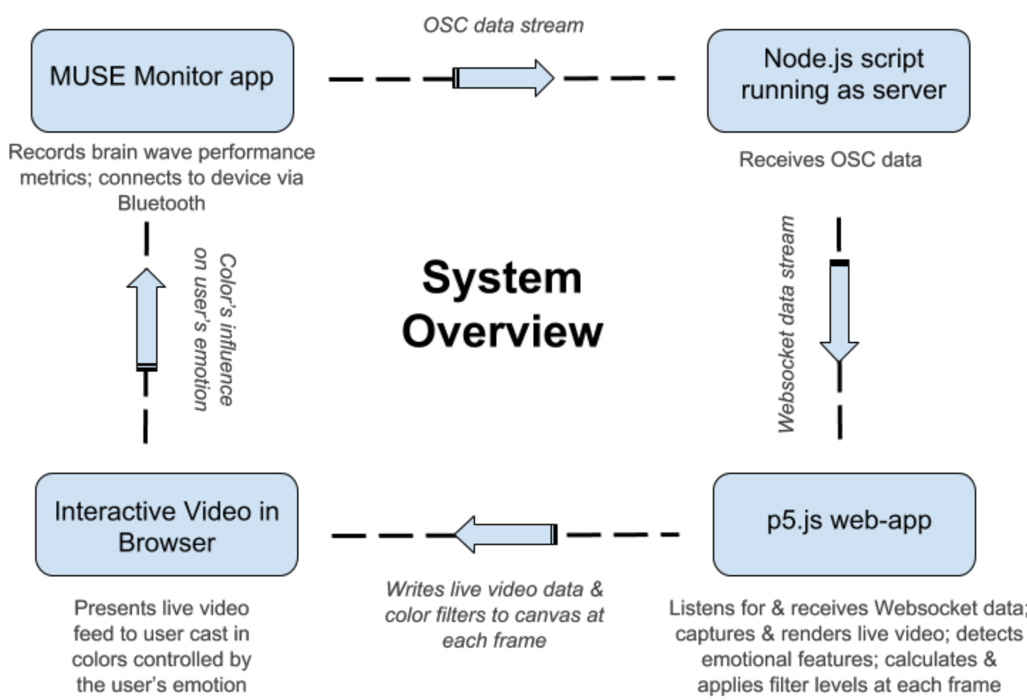

Figure 5: *System overview outlining data processing, streaming, transformation, & visualization*

MUSE Monitor App

Brain waves types (*alpha, beta, delta, theta, gamma*) are classified by frequency channels (measured in Hz or cycles/sec) and amplitude (measured in μV or 1/1,000,000 of a volt). The MUSE Monitor app determines brain wave types from the amplitudes of EEG signals recorded by electrodes on the MUSE headband. The data output by the MUSE Monitor app includes real-time metrics on brain wave performance across all brainwave channels, measured in decibels (dB). For the sake of better understanding the source of the data used to inform this system, it is worth explaining the process by which the MUSE Monitor app generates these brain wave performance metrics.

Due to the complexity of the human brain and the fact that brain wave activity varies across individuals, the MUSE Monitor app scores a user's brain wave performance against his/her own previous brain activity to provide meaningful information about his/her patterns and current state. Frequency powers change logarithmically. Thus, as the frequency of the user's brain waves increase/decrease, the relative magnitudes of the brainwaves are adjusted significantly as well (Farough). This means that recorded changes in brain wave frequencies can hold information regarding the overall *activity* patterns of that brain wave channel. In the context of the MUSE Monitor app, gleaning information relating to the overall activity of a user's brain waves at any point involves a process known as the *Fourier Transform* to translate the raw EEG information from the "time domain", which shows how a signal is changing over time, to the "frequency domain", which shows *how much* of a signal lies within each frequency band over a range of frequencies ("An Interactive Guide", n.d.). In other words, the MUSE Monitor app works to determine the activity level of a user's brain wave activity.

The brain wave activity levels recorded in the MUSE Monitor app are scored relative to their respective wave frequencies and a brief history of the user's brain wave activity range that is stored locally (though the extent of this history which is unclear) (Farough, n.d.). So, for example, an alpha wave score of 0.8 in the MUSE Monitor app means the user's alpha activity level is being rated as 80% against his/her own alpha brain wave performance (Farough, n.d.). Ultimately, the EEG signal processing performed in the MUSE Monitor app establishes a way to systematically classify brain wave performance metrics. These metrics provide the data that directly inform the emotional feature detection process by which the rest of this system operates.

Data Stream Connections

The streaming of live Open Sound Control (OSC), a data transmission protocol, from the MUSE Monitor application to the user's device for use in creating an interactive web-app is enabled by Node.js. Node.js is an open source, cross-platform server framework that uses JavaScript on the server. The speed by which it can serve client requests makes Node.js ideal for generating dynamic page content and developing a data-intensive, real-time streaming application running across distributed devices (Tutorials Point). For this reason, Node.js is important to the design of this system. The data delivery system for this interface can be described as follows: A data stream is established between a Node.js script, running as a server and the browser via a Websocket connection. A separate script makes continuous file requests to the Node.js server. This script listens for and receives Websocket data and delivers this Websocket data to a front-end web-app where it is used to create an interactive video. The reason for this relay middleware app is that contemporary web browsers cannot read OSC data streams directly. However, the Muse Monitor app only outputs OSC. So, the node application relays the incoming OSC data by listening to incoming OSC traffic and relaying those messages in a different protocol (websockets, which are browser native).

Interactive Video Creation

On the front end of this system, the HTML 5 getUserMedia() API is used to capture video from the camera on the user's device (Bidelman). With this, the application renders live webcam data to a canvas where filters can be applied and manipulated at each frame. The p5.js JavaScript library is another critical tool used to create an interactive visual experience for users. The library's full set of drawing functionalities are used to write video frames from the camera of the user's tablet or smartphone to the full screen. Throughout a session, the app calculates emotion related features of arousal and valence from the user's brain wave activity data. Enabled by tools within the p5.js library, the web-application dynamically determines color-related filter levels in real time, including hue, saturation, and brightness, as a function of the user's own arousal and/or valence levels and applies them to the canvas at each frame.

Calibration & Filter Manipulations

To create an interactive video that dynamically responds to a user's emotional state, differences and variations amongst individual users must be identified and factored into the design. As pointed out earlier in this paper, brain wave activity typically varies across individuals and may vary for the same individual in different contexts. It would therefore follow that, for how they are considered in this interface design, so too do emotional features. To account for this, the first 30 seconds of a session calibrate the system. During this 30-second calibration period, the system interprets and stores information on the unique brain wave behavior for the user and adjusts accordingly. With this, the system establishes the relationship between the individual user's emotional features (arousal and valence) and color qualities (hue, saturation, and brightness) in a given context.

Throughout the 30-second calibration period, the user's maximum and minimum arousal and valence levels are continuously stored and updated. After 30 seconds, the range of the minimum and maximum values for each of the two emotional features are stored permanently until the user recalibrates the system. Using the p5.js library's *map* function, the ranges of the user's arousal and valence levels are re-mapped to the range of the preset color filter levels they directly impact (saturation for arousal & brightness for valence). The hue-rotate value is there forth determined as the angle of rotation from the origin to the user's emotional coordinate on the AVS plane. Each of these calculations is illustrated below:

Saturation (%) = map(arousal, min_arousal, max_arousal, 10, 600)

Brightness (%) = map(valence, min_valence, max_valence, 50, 150)

Hue-rotate (°) = atan2([saturation-100], [brightness-100])

With this design, the calibrated system adapts to the individual user's unique brain wave activity and emotional features for a given session. The calibration period establishes emotional boundaries and extremes for an individual, recognized by the system throughout the time it is listening. This design seeks to enable every user the potential to experience the full range of color consequences possible while immersed in this interface system. Even though brain wave activity and emotional feature levels might vary across users, the calibrated system detects and responds to a full range of emotional states for every user.

Discussion:

Methodological Implications and Limitations:

It is important to point out that the design of system does not seek to define or classify users' emotional states by the color consequences elicited. The filter types (hue, saturation, and lightness/brightness) have been chosen for their representation of the dimensions of human color space (Purves, 2011, p.61). There is no precedent or direct research informing the mapping of saturation as function of arousal, lightness/brightness as a function of valence, or hue as a function of both arousal and valence, nor am I suggesting that such correlations exist through this thesis. The color qualities produced by the system's measuring of arousal and valence are not meant to indicate direct links between particular colors and emotional states. The implementation of these color qualities into the design are instead based on preferential choices to create an interesting visual experience that achieves the goal of putting the user's perception of color in a unique dialogue with his/her emotions.

Furthermore, the limitations of the process by which the system is calibrated to the individual user's unique brain wave activity and the emotional feature characteristics should be acknowledged. The 30 second calibration period takes place at the start of each session and the system can only be recalibrated if and when the user chooses to do so. While the theory behind this design choice is appropriate for the way it is considered in this project, the current calibration process does expose some potential weaknesses in the system. With the current design, the system only "listens" and adapts to patterns exhibited by an individual user for a short time period. The user's experience throughout the rest of the session is shaped by the information gathered within this short calibration period. This process assumes that a user's brain wave activity and emotional features can be meaningfully characterized within this time frame and that these characterizations can be translated beyond the 30 second calibration period. Further research is necessary to explore these potential weaknesses. Doing so involves developing new methods for examining the extent to which the characteristics of brain wave activity and emotional features can be captured within a given time period and if that characterization can be translated for one individual over a period of time.

Lastly, it is also worthy to reinforce that this generative system works to immerse users in a biofeedback loop and should not be considered as simply a projection of the user's emotions. In the context of this system, the user's emotional state and color work bi-directionally on one another. The system's reading of the user's emotional state dynamically determines the color qualities of his/her view of the world while the user's perceptual experience of color under these circumstances may simultaneously influence his/her emotional state in ways yet to be determined. This aspect of the design is what principally separates this model from others exploring the relationship between color and emotion. However, it also raises further challenges in considering how any data recorded on the experience of the user, whether it be metrics on the color effects experienced by users or their emotional state changes, should be analyzed or interpreted to provide valuable insight into the relationship between color and emotion.

Conclusion/Future Direction:

This project accomplishes the goal of building an interface system that prompts the user to confront and subconsciously reflect upon the complexity of the relationship between color and emotion. With its current design, the system might also be applied to create more interesting experiences. For example, emotion-related data gathered by the system can be recorded, stored, and fed back into the system to present a video cast in the colors of a previous emotional experience. Such ideas are to be considered for future iterations/demonstrations of this project.

The challenges confronted and the methods adopted in the design of this interface system also demonstrate the potential as well as the limitations of current models for emotional classification. For example, the lack of any perfect way to capture a central state of arousal & valence that can be translated over any period of time, presents a challenge to be considered in calibrating this system. Future studies might shed light on more accurate methods for capturing and evaluating emotional features for an individual over time and within a given context that might improve this process.

The broader goal beyond this project is to continue to create systems where individuals interact with/experience color under new circumstances that could potentially reveal new dimensions or lead to new ways of modeling the relationship between color and emotion. However, meeting this broader goal requires further research. Controlled behavioral and observational studies assessing this interface's impact on user response to stimuli might work to better understand the perceptual implications of the biofeedback loop this system establishes. Moving forward, it would also be useful to conduct data analysis studies on the data generated by the user's engagement with this system. This might include analysis on user brain wave activity while immersed in this system or data recorded on the color manipulations they experience. Developing systematic ways to draw inferences from any patterns or correlations that might exist for individual users or across multiple users could provide potentially valuable insights into the color-emotion relationship that might inform future iterations of this project.

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