NEURAL CHARACTERIZATION OF THE IMPROVISATIONAL CREATIVE PROCESS

by

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Abstract

Mobile Brain-Body Imaging (MoBI) enables the study of the human creative process in freely-behaving participants in natural settings. Past studies on human creativity rely on neuroimaging technology that requires participants to remain in a confined, motionless space. This limits the study design to static, queued actions that oversimplify creative actions. Other studies rely on psychometric tests that compare scores to brain activity at rest, which cannot claim a specific bearing on the creative process.

The main goal of this dissertation is develop novel experimental and analytical approaches to assay the human creative process in natural settings. To accomplish this goal, developed two experiments: 1) We examined the creative process in professional visual artists working collaboratively, in an adaptation of the Exquisite Corpse surrealist game; 2) we examined neural data of college students as they created compositions before and after a 16-week creative writing workshop. These experiments aim to identify and characterize neural features associated with the highly dynamic creative process. We used frequency-domain, time-domain, and functional connectivity features from scalp Electroencephalography (EEG). Both classical machine learning and deep learning approaches were deployed to identify the most relevant features.

Two major findings were obtained. First, the functional connectivity analysis identified patterns between right parietal with left central-frontal scalp areas during creative execution, which were enhanced with experience. Second, the machine learning methods successfully classified neural EEG data in both studies. In the Visual Arts experiment, the classification accuracy reached $53.5 \pm 2.4\%$ for 5-classes: two rest conditions, planning, mark making, and writing. In Creative Writing, the classification accuracy reached $79.3 \pm 3.1\%$ for 4-classes: two rest conditions, transcription, and creative writing.

Overall, these findings suggest that creative execution tasks can be characterized by a state of long-range cortico-cortical communication between multisensory integration in temporal and parietal brain regions and high-order execution and planning areas in frontal regions of the brain. This dissertation provides evidence for common information flow patterns in professional visual artists and student writers matching increased flexibility for creative evocation. In conclusion, this approach provided a better understanding of the human creative process through neural feature characterizations in real world settings.

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Chapter 1

Introduction

The development of Mobile Brain-Body Imaging Technology (MoBI) with mobile Electroencephalography (EEG), motion sensing, and novel denoising algorithms, comes as a promising tool to study the neural dynamics of creative activities in contextually relevant settings. The technological development in hardware wireless portability, signal quality, on-device or cloud storage, and data-processing techniques enable the study of natural cognition in real world settings. This dissertation discusses recent advances in the field of MoBI technology implementation led by the Laboratory for Noninvasive Brain-Computer Interface Systems at the University of Houston, for context-relevant experiments that aim to investigate the human creative process with freely behaving participants acting on natural, real-world settings. This approach brings the neuroscience closer to examining authentic aesthetic experiences through improvisation, idea gestation, and education. The experimental protocols described here provide opportunities for the creative process to occur naturally and in response to context-relevant queues.

MoBI technology enables, for the first time in the study of the human creative process, the possibility of its study in freely-behaving, natural settings [1, 2]. The studies reported in this dissertation provide neuroscience data and findings that contribute to the discussion of the neural features associated with real-world creative production. The results and discussion provide empirical neuroscience data, while at the same time providing evidence for the use of MoBI in real-world settings to investigate the human creative process.

The conception of creativity with which we work here relates to an individual's ability to produce a composition, object, artifact, sensory experience, act or thought that is novel, timely, with reward-eliciting attributes (valued), and relevant within a socio-cultural context. This definition is consistent with the usage of the term in the neuroscience literature (e.g., [3, 4, 5, 6, 1]).

The nature of the human aesthetic experience, both in the production and contemplation of art has been extensively discussed among a range of academic disciplines including philosophers, historians, anthropologists, artists, and more recently by neuroscientists. The inclusion of the latter has been not been without controversy and skepticism [7] from established schools of thought, but nevertheless a valuable addition in the quest to understand the human creative process with empirical neuroscience data. As neuroscientists, we aim to apply the methods of our field and support our conclusions with empirical data to supplement the overarching discussion of the neural basis of the human creative process. Findings in the field of freely-behaving neuroscience will provide complimentary bottom-up (data based) ideas in the conversation about the human creative process; while the collaboration, both in experimental design, and interpretation of results from experts in their field, provide a much-needed top-down perspective to build a balanced body of knowledge from which to develop cognitive neuroscience models and hypotheses for further study.

From Zeki's seminal work on the field [8], the study of neuroaesthetics has produced valuable knowledge in the neurobiology of the aesthetic experience. In response to Guilford's call [9] for the study of creativity, psychometric tests had dominated the study of human creativity for well over 60 years, often equating concepts such as divergent thinking as a proxy for creativity; a practice that has produced varied results and has been strongly questioned [10, 11, 12, 13]. The field has since expanded to encompass not only "aesthetic" elements, or the use of standardized psychometric tests that study elements of human creativity, but also to study creative production and contemplation as a process, in experiments that move closer to authentic creative reflection.

Although neuroscience findings have been varied and inconsistent in the study of human creativity, the modulation of activation in the pre-frontal cortex for creative tasks [10] appears to be a common denominator in the literature. In 2014, Fink and Benedek [14] reviewed the neuroscience in creativity literature and found robust evidence of EEG alpha power (8-12 Hz) across the scalp being sensitive to creativity task demands, and creativity level measured through psychometric tests. Their findings suggested that increased alpha during in creative ideation was the most consistent finding in the neuroscience literature based on EEG. Later that year, the same group of collaborators reported on increased functional connectivity at rest, using fMRI and divergent thinking tests, between the inferior prefrontal cortex and the default network in highly creative individuals [15].

As research on human creativity advanced both in findings and critical revision of protocols, the deployment of MoBI technology in mobile, freely-behaving individuals, had reached important milestones that allowed for its implementation in real world settings. In 2013, time-domain feature algorithms were developed by our research group to decode movement intent from EEG data into commands to control an overground exoskeleton [16, 17, 18]. These algorithms were implemented to investigate the feasibility of decoding expressive movement based on Laban Movement Analysis effort qualities through EEG data only [19]. In 2015, we conducted the first MoBI experiment in a museum setting, analyzing brain activity data from over 350 museum goers at the Menil Collection [20], where we were able to classify the kind of artwork (based on image processing features) the participants were experiencing, all from EEG data. We also found that functional connectivity in the gamma band increased substantially during artwork viewing compared to rest, connecting parietal to frontal areas. Further research explored the characteristics of such EEG real-world data [21]], potential artifacts that hinder data collection, and overall suggestions for data acquisition [22]. These advances, both in protocol and quantifications of the human creative process by our group and others, placed us in an ideal position to explore the human creative process in action and in context: in real world settings through MoBI.

1.1 Overall Goal of This Dissertation

One hypothesis that motivated the research on the human creative process through MoBI in real world settings is that there may be common neural features or neural markers characterizing creative production, across artistic domains, and across participants [1]. To validate this hypothesis, we implemented the same feature extraction mechanisms across the experiments discussed in this dissertation. The features found pertaining to different stages of the creative process, both through an improvisational creative production task, and through the length of a semester-long creative writing workshop, allow for new knowledge in the characterization of proper feature dynamics in the field.

In the improvisational visual arts experiment (Chapter 6), we analyzed the band power and connectivity features in a detailed discretization of creative actions performed by the artists in order to complete their composition; based on elements of drawing and collage. High connectivity patterns emerged in execution tasks: mark making, and highest in writing, even when writing included pasting letters in semantic patterns on the artwork. The connectivity patterns linking linking right parietal with left central-frontal areas of the scalp electrodes emerge in opposite directionalities in the creative phases of preparation (frontal to parietal) vs generation (parietal to frontal) of creative texts (Chapter 7. These patterns are highest during creative writing production, and consistently higher after physically experiencing the writing process, and skill development (Chapter 8).

With machine learning classification techniques, we tested the relevance of the features proposed and accurately classified creative actions based solely on EEG features. This was corroborated with automatic feature selection and classification using Deep Learning, in which the algorithm automatically found relevant features in the data for classification, and our feature visualization techniques shed light onto the features that most contributed to classification performance.

1.2 Dissertation Organization

This dissertation is organized into ten chapters. The introduction outlines the motivation, background, and scientific questions that we aim to address. The work described here is inherently multidisciplinary, as it lies at the intersection of neuroscience, engineering, and theory of creative production; providing ample opportunities for broader impacts in education, creative outputs, scientific outreach, collaborations.

Chapter 2 establishes the specific aims of this dissertation.

Chapter 3 presents the overall data analysis methods in signal processing and machine learning used throughout the dissertation.

Chapter 4 addresses the implementation of trans-disciplinary experimental design, a major scientific proposal in the study of the neuroscience of the human creative process [1], put forward through this dissertation. We discuss how the experimental protocol of the Exquisite Corpse was implemented. We address to what extent the sense of authenticity was obtained, from the artsits' perspective, as well as the new possibilities and limitations of the neuroscience study of the human creative process in this unconstrained behavioral setting.

Chapter 5, overviews the rationale and the experimental design for the implementation of EEG recordings into a real-world creative writing workshops. The chapter explains the experiment and workshop design, and how they relate to current philosophy in creative writing as an embodied process. We address the question of authenticity in the study of creative writing.

Chapters 6, 7, and 8 discuss experiments implemented to meet the specific aims.

Chapter 6 discusses a collaborative experimental design between neuroscience, engineering, and the visual arts, in which we created an experimental protocol that aimed to analyze the improvisational human creative process using MoBI. The protocol was based on the Exquisite Corpse, a game invented by the surrealists in the 1920s. A feature extraction and machine learning data analysis for MoBI in freely-behaving settings is proposed, comparing classical and automatic feature extraction methods and testing their performance in a classification scheme to characterize the human creative process in terms of neural features associated with creative task labels that aimed to discretize the creative process of six artists in the visual arts.

Chapter 7 discusses a pilot study that moves forward with the idea of using MoBI to characterize the human creative process in real world settings, for creative writing. We developed a MoBI-integrated creative writing course in which students wore MoBI devices to track their brain activity as they walked and experienced the city of Houston, and as they created their first drafts of creative texts. The findings from this study, both in protocol performance and in neural features, provided the basis for the experiment discussed in the following chapter. The same feature extraction methods from Chapter 6 were used here to characterize the neural dynamics driving the creative process of the students.

Chapter 8 is an experiment on creative writing in which four EEG data collection sessions occurred during the course of a 16-week creative writing workshop. Before the workshop, the students were set up with MoBI data collection equipment and given writing prompts as pictures. During the workshop the students physically experienced the writing prompts (locations in Houston), and their community; and wrote creative texts from them. Those texts were discussed as a group during workshop hours. Two of those discussion sessions were equipped with MoBI technology. Finally, at the end of the workshop, the students went through the same creative writing prompts again, now with bodily experience in those locations. This chapter analyzes the change in neural features from Before and After the workshop using the writing prompts. The same feature extraction and classification methods as in Chapter 6 were used for data analysis.

Chapter 9 draws conclusions from the experiments and results described in Chapters 6-8. It brings together the main findings and evaluates how these findings relate to previous studies on the human creative process. Crucially, this set of experiments is the first to analyze the human creative process in real world, mobile settings. We propose how these results further enhance existing models of the human creative process, and the possibilities for the implementation of MoBI technology for further inquiry.

Chapter 2

Specific Aims

This doctoral dissertation contains two specific aims:

Aim 1: Characterize the neural basis of the creative process during collaborative improvisation in the visual arts.

Through the re-adaptation of the surrealists' game, The Exquisite Corpse, we propose an experimental protocol that aims to capture the human creative process in the visual arts in a real-world setting. Three professional artists participated in the experiment, incorporating elements of drawing and collage, as well as chance, improvisation, and collaboration. The experiment was run for two sets of three artists. Gel-based 64-channel EEG captured their brain activity, while motion sensors in the arms and head captured kinematic information associated to their creative production, and three video cameras recorded the session for creative action annotation (by human annotators). The protocol was developed in collaboration with professional artists in an effort to achieve an authentic creative experience from the point of view of the artists, and a neuroscientific study protocol that would enable us to understand the neural dynamics associated to the improvisational creative process in the visual arts.

EEG features in the frequency-domain, time-domain, and functional connectivity were extracted to characterize the creative process of the artists. The feature relevance was evaluated by comparing the time-course of the features with the creative action annotations (class labels) by means of mutual information. With the selection of relevant features, the neural data was automatically classified using support vector machines (SVMs).

This method was compared with an automatic feature extraction method using convolutional neural networks (CNNs) to find potential features of interest without explicitly defining those features. We expected to uncover cortical patterns that drive the dynamic cognitive processes involved in creative expression.

A successful automatic classification of EEG data associated to distinct phases of the human creative process would validate the relevance and robustness of the selected features. Classification performance was expected to provide insight into the information shared between the tasks analyzed, and therefore into the nature of the cognitive processes involved at each stage.

The selected features were evaluated across artists, emphasizing the analysis on the common neural features associated to the artists' creative process as a group. The training and validation sets were taken from all artists. The test set was taken from temporally isolated data samples; providing classification results for pseudo-real time classification for an assessment of prediction power of this machine learning scheme for visual artistic production.

Aim 2: Characterize the neural basis of creative writing during a semester long, upper division college-level creative writing workshop.

This experiment analyzed the neural features associated to the creative writing process in two experiments: a pilot study that involved mobile EEG, and an in-class experiment with four data recording sessions across a 16 week workshop. The purpose of these studies was to characterize the human creative writing process in non-expert students, and assess changes in the neural features associated with it after training and experience provided by the workshop.

The pilot study assessed the implementation of mobile neurotechnology in a real-world creative writing workshop setting where students had to walk move through physical spaces before creating their drafts; and collecting their EEG data throughout those experiences. This study provided information on neural feature candidates to use for creative writing characterization across students.

In the second creative writing study, classical and automatic feature extraction algorithms were implemented to characterize the neural dynamics associated to creative writing, across students. The predictive power of the features found was assessed through classification performance. Those most relevant features were compared before and after the 16-week workshop to track changes in the neural processes associated to creative writing that emerge from training: writing drafts, and physically placing their bodies through specific experiences (the writing prompts).

Chapter 3

Data Analysis Methods

This section describes the main statistical data analysis methods implemented throughout the dissertation.

3.1 EEG Band-Power Features

Frequency band power features is one of the most common representations of EEG signals found in the EEG literature [23]. Band power features represent the EEG data in terms of their power in a given frequency band per channel over a selected time window. In the experiments described in this dissertation, the pmtm() [24] function in Matlab was used to calculate band powers; with time-halfbandwidth product $nw = 4$. The band power features were calculated for five typical frequency bands in EEG analysis: Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz), and Gamma (30-50 Hz).

3.2 EEG Partial Directed Coherence (PDC)

Functional connectivity is defined as the statistical association among two or more distinct time-series and can be assessed with EEG coherence measures [25, 26]. Functional connectivity analysis was performed upon our EEG channels by computing the PDC measure [27] in data windows under six seconds in length, known as the short-time PDC measure [28]. PDC measures have been found to perform well with low-density EEG [29].

PDC is based on the concept of partial coherence [27], a technique that quantifies the relationship between two signals while avoiding volume conduction. Volume conduction is regarded as the most critical issue of traditional coherence. PDC measures directional (i.e. causal) influences between the signals. PDC is formulated using Multivariate Autoregressive models. PDC is calculated as shown below [30]:

If we have a set of n time series simultaneously recorded, $\boldsymbol{x}(t) = [x_1(t), ..., x_n(t)]^T$ can be represented by an autoregressive model or order p:

$$\boldsymbol{x}(t) = \sum_{r=1}^{p} \boldsymbol{A}_r \boldsymbol{x}(t-r) + \epsilon(t)\,, \tag{3.1}$$

where $\boldsymbol{A}_r$ is the coefficient matrix at time lag r with elements $a_{ij}(r)$, where $i, j = 1, ..., n$; and $\epsilon_1(t) = [\epsilon_1(t), ..., \epsilon_n(t)]^T$ is a vector of Gaussian white processes with zero mean and covariance Σ. The autoregressive coefficients $a_{ij}(r)$ represent the information flow from $x_j(t-r)$ on $x_i(t)$. We can regard PDC as a frequency-domain description of Granger causality [30, 31, 27].

For PDC, we define the matrix $\bar{\boldsymbol{A}}(f) = \boldsymbol{I} - \boldsymbol{A}(f) = [\bar{\boldsymbol{a}}_1(f), \bar{\boldsymbol{a}}_2(f), \bar{\boldsymbol{a}}_3(f)]$. Here, the elements $a_{ij}(f)$ form the Fourier transform of the elements $a_{ij}(r)$. The elements $\bar{a}_{ij}(f)$ are the columns of $\bar{\boldsymbol{A}}(f)$. The PDC from channel j to channel i is defined by

$$\pi_{ij}(f) = \frac{\bar{\boldsymbol{a}}_{ij}(f)}{\sqrt{\bar{\boldsymbol{a}}_i^H(f)\bar{\boldsymbol{a}}_j(f)}}\,, \tag{3.2}$$

where H denotes the transpose and complex conjugate operation. PDC $\pi_{ij}(f)$ is bounded between 0 and 1.

3.3 EEG Sample Entropy

Time-domain features have been extensively used in the EEG literature for motor [17, 18, 32, 33] and expressive movement task classification [19, 34]. These features typically involve a concatenation of data across channels, and time-delays to compute, or are implemented in a sample-by-sample prediction basis. Other time domain features such as measures of central tendency (e.g. mean, variance, kurtosis, etc.) tend to correlate with frequency band power features .[35]. We decided to test complexity measures as potential features of interest to exploit the non-stationarity characteristics of EEG data.

Approximate Entropy (ApEn) is a measure of signal regularity which was first proposed by Pincus, that explores the time ordering of data points by calculating the log likelihood that runs of pattern which are close remain close for incremental comparison [36]. Lower value of ApEn indicates that the signal is more regular or predictable. However, studies have reported reliability issues using ApEn due to the self-match involved in ApEn computation leading to a bias [37, 38]. Sample entropy (SampEn) is a metric developed addressing the bias issue of ApEn [37]. The parameters remain the same for both ApEn and SampEn: the "filter factor", r, length of sequences being compared, m, and the signal length, N. SampEn has shown to be less dependent on the signal length and shows better stability for wider range of parameters m, r,and N [39]. For a time series X of length N, $X = x_1, x_2, ..., x_N$. We define the template vectors X_i and X_j,

$X_i = x_i, x_{(i+1)}, ..., x_{(i+m-1)}$,

$X_j = x_j, x_{j+1}, ..., x_{(j+m-1)}$,

$1 \leq j \leq N - m + 1, j \neq i.$

The sample entropy is defined as

$$SampEn(m, r, N) = -log(U^{(m+1)}(r)/U^{m}(r), \tag{3.3}$$

where

$U^m(r) = (N-m)^{-1} \sum_{i=1}^{N-m} C_i^m(r)$,

and

$C_i^m(r) = B_i/(N-(m+1))$.

Here, B_i is the number of vector pairs at which the distance $d|X_i, X_j| < r$.

Earlier studies showed that SampEn gives better statistical validity for $m = 2$ and the r in the range of 0.1-0.25 [40, 41].

3.4 Feature Selection

The most relevant features across subjects were selected using a mutual information implementation of the maximum relevance minimum redundancy (mRMR) [42] algorithm. In mRMR, a feature score is sequentially calculated by computing the mutual information between each feature and the target/class vector; and subtracting the redundancy term: average mutual information between each remaining feature and the previous selected features.

$$\text{mRMR}_{score} = \max_{x_j \in X - S_{m-1}} \left[I(x_j; T) - \frac{1}{m-1} \sum_{x_i \in S_{m-1}} I(x_j; x_i) \right]. \tag{3.4}$$

In the mRMR score equation above, x_j is the j^{th} feature being tested, X is the set of all features, S is the set of selected features, T is the target/class vector, m is the number of remaining features, and x_i is the i^{th} remaining feature being tested. The features were sequentially selected based on the performance on the training set. The first term is the mutual information between the discretized feature x_j and the class vector. The second term is the average mutual information between the discretized feature x_j and the previously selected features $x_i \in S_{m-1}$.

3.5 Classical Machine Learning: kSVM

The classical machine learning classifier used for the EEG and motion data was the kernel support vector machine (kSVM), using the polynomial kernel of degree 3. The value of the and box-constraint was set to 1 in all cases.

The polynomial kernel of degree 3 for SVM was used in all cases, as it provided the best classification accuracy in all cases described in this report: EEG feature classification in the Exquisite Corpse for the visual arts (chapter 6), and in the creative writing task (chapter 8). The classifiers compared were: Linear Discriminant Analysis, Quadratic Discriminant Analysis, Linear SVM, kSVM polynomial degree 2, kSVM polynomial degree 3, kSVM with radial basis function (Gaussian) and a range of spread values from $\sigma = 0.5$ to 20.

Classical machine learning techniques involve a combination of hand-crafted features, based on previous neuroscience, to approach the problem. These features are then set as input for a classifier. We used band power features for each channel and PDC between all channel pair combinations as features, in 4s windows with 50% overlap. The features obtained in each of these data windows constitutes constitute a data sample. The data samples from all subjects were analyzed together. We selected randomly, with repetition, $N_s = 300$ samples per class, to achieve class balance.

The training, validation, and test sets were divided temporally. The data from the first temporal 80% of the experiment was selected for the training and validation sets, while the last temporal 20% was selected for the test set. From those samples, ($N_s = 500$) samples were selected to achieve class balance, divided into ($N_s = 400$) samples for the training and validation sets, and ($N_s = 100$) for the test set.

3.6 Automatic Feature Extraction: Convolutional Neural Networks (CNNs)

CNNs are structured with a series of convolutional and pooling stages prior to one or more fully-connected layers. Individual units of a convolution layer are organized into feature maps, which link a specific unit to local patches of the feature map from the previous layer through a collection of shared weights called a filter bank. The filter banks necessary to perform these convolutions are automatically adjusted through back-propagation.

The pooling layers combine features from the convolutional layer into a smaller set of features. The use of local receptive fields, weight sharing, and pooling layers helps to reduce the high dimensionality of EEG data [43]. Additional conceptual information on CNNs can be found in [44, 45].

Deep Learning (DL) can be defined as a computational graph with multiple computation layers that learns the representations of the data [46]. The depth of a model promotes the reuse of important features and could also lead to learning more abstract features at the higher layers where the underlying representations of the data are extracted [47]. The effectiveness of such abstract feature learning can be seen in breakthroughs in numerous domains such as speech recognition, visual object recognition, and genomics [48], and in EEG implementations [49, 44, 50].

A key advantage of DL is in its ability to extract meaningful features[48] without having the researchers hand-craft the features. In the ideal case, this would reduce or eliminate the need for feature engineering that relies on extensive domain knowledge. This would enable learning of different representations, some of them yet unknown in specific domain knowledge.

Deep Learning in EEG Applications

Most EEG + DL studies are merely exploring the possibility of borrowing neural networks from other domains and applying them to EEG. Fundamentally, there are two issues that hinder the usability of DL in EEG data [49]: 1) the size of the EEG dataset is usually much smaller compared to the open sourced data in the DL community 2) EEG is implicitly noisy, which is hard to address with DL models alone.

Recent reviews by our group and others summarize recent studies on EEG and DL [44, 49, 51]. Within the EEG analysis community, Convolutional Neural Networks (CNN), Deep Belief Machines, Recurrent Neural Networks and, Long-Short Term Memory networks, have gained popularity in the past five years [44].

These DL algorithms have been applied to a variety of EEG classification tasks.

Specifically, in Craik et. al. 2019, we analyzed 90 studies, the majority of EEG classification studies were grouped into six general categories: emotion recognition, motor imagery, mental workload, seizure detection, event related potential, and sleep stage scoring applications [44]. Studies were analyzed by type of task and recommendations were given on the types of DL architectures that showed the greatest promise towards successful classification. Outside of these six general categories, there have also been attempts to use DL algorithms to improve our understanding of Alzheimer's disease, depression, bullying indices, and gender classification.

Although in Roy et al. 2019 [49], the authors report that there is a gain of 5.4% in classification accuracy when comparing DL vs classical machine learning approaches, they warn the reader that the studies would be hard to replicate due to the unavailablility of the code and the data. Therefore, results without the code and availability of the data should be taken with additional constraint, as some there are examples in the literature where machine vision researchers attempt to apply the same methods to EEG data without proper denoising strategies, leading to questionable results [52].

In Craik et. al. 2019 [44] we provided recommendations on the specific architecture designs for CNNs and other types of DL approaches. CNNs with four convolutional layers outperformed other formulations when signal values were used as inputs, whereas CNNs with two convolutional layers outperformed other variations when images were used as inputs.

The proposed CNN architecture (Fig. 3.1) for the purpose of this report is a 6-layer architecture with one temporal convolutional layer and one spatial convolutional layer. We aim to resemble typical EEG feature extraction strategies [23]: frequency bank information, followed by spatial combinations of electrodes (such as in ICA, PCA, etc) [50]. The temporal layer aims to extract temporal and frequency-related information from the EEG signals, for each channel separately, projecting to a number of filters. Then, a spatial convolution combines the information from all of the channels at each time point, and projects it down the CNN layers. A Max Pooling and a Fully connected layer, with 20% dropout for stochastic robustness, lead up to the Fully Connected Softmax Classification layer.

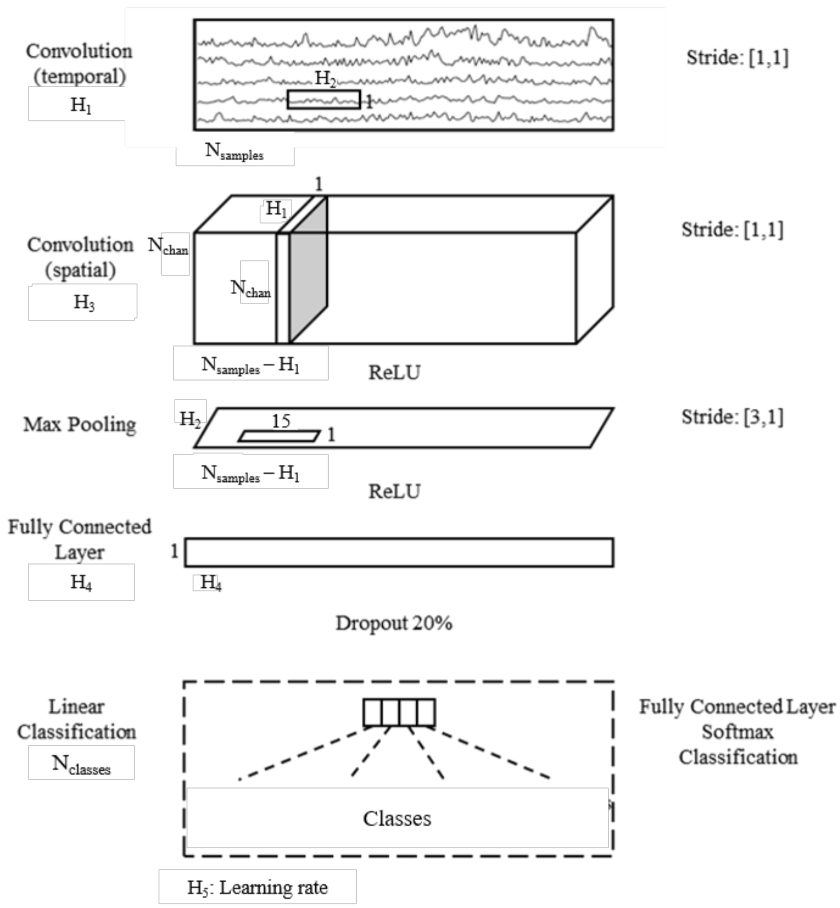

Figure 3.1: CNN Architecture. Hyper-parameters to be optimized: temporal filters H_1, length for time convolution H_2, spatial filters H_3, nodes in fully connected layer H_4, and the learning rate H_5.

Chapter 4

Your Brain on Art: A New Paradigm to Study Artistic Creativity Based on the 'Exquisite Corpse' Using Mobile Brain-Body Imaging. Experiment Design and Rationale.

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4.1 Abstract

We propose a novel experimental paradigm to investigate the human creative process in artistic expression using mobile brain-body imaging (MoBI) technology, which allows the study of brain dynamics in freely behaving individuals performing in natural settings that promote authentic artistic experiences. Our proposed multimodal experimental protocol is based on the 'Exquisite Corpse'—a collaborative, chance-based game created by the Surrealists in the 1920s. In this protocol, three artists collaborate to create the start, middle, and end of an improvisational piece of artwork, which can be implemented across artistic domains, including the visual arts, dance, music, creative writing, acting and even gastronomic art. Performers are instrumented with wireless scalp electroencephalography(EEG) to record brain activity and inertial measurement units (IMUs) to capture body movement, while video cameras capture the evolving gestures of the participants and the art pieces. Sample adaptive denoising algorithms, computer vision, visualization, sonification and machine learning methods allow for the pre-processing, tagging, parsing, storing, aggregating, analyzing, and sharing of complex containerized multimodal data. These MoBI data and associated behavioral, cultural, demographic, and situational data collected under the Exquisite Corpse paradigm holds the promise of a better understanding of functional (affective, cognitive, and motor) and dynamic brain processes, the study of the neuroscience of individuality and group behavior, and the design of robust affective and artistic brain-computer interfaces (BCI) and other diagnostic and therapeutical devices.

[1]The figure captions were modified to comply with dissertation format guidelines from the Department of Electrical and Computer Engineering, University of Houston.

Keywords: Creativity, EEG, MoBI, Creative process, Neuroscience, Neural interfaces, BCI

4.2 Introduction

The nature of the human creative process, both in the production and contemplation of art has been extensively debated among philosophers, historians, anthropologists, artists, and more recently neuroscientists. The inclusion of the latter has been not without controversy and skepticism from established schools of thought [7, 53], but nevertheless, neuroscience studies have provided alternative and often competing approaches and tools for understanding the neural underpinnings of the human creative process with empirical neuroscience data and methods. More recently, computational neuroscience and advanced mobile brain-body imaging (MoBI) technology to record the brain and the body "in action and in context" have allowed researchers to study the dynamic brain of freely behaving individuals in complex natural and creative settings [20, 2]. The underlying framework is that by engaging in meaningful collaborations at the nexus of the arts, science and engineering, emergent bottom-up (data-driven) and top-down (e.g., from first principles) analyses, complemented by input from artists and philosophers, can lead to reconciliation of high-level personal perspectives, and a balanced body of fundamental knowledge from which to build models and hypotheses for further study.

The development of MoBI technology, typically comprised of mobile scalp electroencephalography (EEG) and/or functional near infrared spectroscopy (fNIRS) and motion sensors in its simple technical instantiation, has made it possible to study directly human brain activity (or indirectly via measurement of blood oxygenation profiles from the surface of the scalp with fNIRS) in unconstrained and freely behaving individuals acting in real world settings [35, 22]. MoBI experiments require the integration of synchronized mobile bio-sensor technology for brain and body data collection, and context monitoring devices such as video and event tagging.

Along with the capability of studying freely behaving participants in complex settings over short or long periods of time, MoBI technology provides the means to study brain responses in a wide range of subject populations encompassing healthy participants, people with a history of neurological disease, children, older adults, and it allows for the participation of spontaneous volunteers in public spaces [20, 35, 22, 54, 55]. IMUs on the headset itself and on the participants' bodies enable for acceleration, magnetometer, and gyroscope data to be collected to understand both how users move through and navigate space, and to help identify potential motion induced artifacts on the EEG signals [56]. Additionally, electrodermal activity, electromyography, electrooculography (EOG), heart rate monitoring, and virtually any biosensor that can be synchronized to the brain-monitoring device enables the measurement of embodied physiological contextual components of behavior. Finally, video cameras, motion tracking sensors, machine vision, and human annotators provide the context-awareness mechanism that enables the systematic study of neural and body dynamics in complex natural settings. As such, the sensors in concert with computer vision algorithms provide valuable contextual information for labeling the brain-body data according to environmental cues, movement type, or tasks to mention a few possibilities.

4.2.1 Chapter Organization

This chapter provides an overview of neuroscience research in the human creative process and recent developments in MoBI data collection that allow for its study in freely moving, real world settings. First, we highlight neuroimaging studies that provide evidence for the human creative process as emerging from the interaction of affective, cognitive, and movement-related processes, and brain areas associated to them. Second, we propose an integrative experimental protocol that allows the study of the production of an artistic composition implemented across artistic domains, where the artists create in a freely moving environment. Third, we provide an example of a data analysis technique to extract important features in an artist's individual creative process. Then we discuss how such an experimental protocol addresses the question of authenticity in the study of creative production. Finally, we consider how neuroscience knowledge gathered in authentic creative experiences can enhance artistic BCIs.

4.3 In Search for a Universal Model of the Human Creative Process

4.3.1 From the Mystical to the Neural

Initially regarded as the product of a "mystical" mental state, or of an unexplainable "divine intervention," creativity during and before the early nineteenth century was largely understood as a spiritual process—one that was untouchable by the grasp of scientific reasoning or study, and only experienced by those who were able to use another worldly introspection to create product from inspiration [57]. From viewing creativity as an inaccessible, ethereal state, the early twentieth century paved way to understanding creative thinking by means of a theoretical lens—a movement that heavily relied on a psychodynamic approach of study.

This approach was not only headed by Freud, who popularized the psychoanalytic theory and pointed to the importance of the emergence of unmodulated thoughts in consciousness, but also highlighted the idea that creative thought arose from the tension between reality and unconscious motivations. While this approach could be regarded as successful in pulling creativity out of its mystical background and into a more scientific realm, this method of study relied largely on tightly-controlled laboratory settings keeping this progress in creativity research somewhat isolated. Consequently, some of the first truly objective, measurable, and widely-applicable research on creativity was incited by the 1950 American Psychological Association Presidential address [9] delivered by J.P. Guilford, who not only emphasized the prevalence of creativity in "everyday subjects" and proposed that this phenomenon could be studied through simple paper-and-pencil tasks, but also propagated the distinction between convergent and divergent streams of thinking [57, 58]. Utilizing methodologies such as the Unusual Uses or Alternate Uses tests (i.e., how many uses are there for a brick?), Guilford jump started creativity research, proposing ways in which individuals' creative abilities could be measured and placed on a standard scale. This approach, however, was only meant as a starting point for the field. While some of these psychometric measures are still being used within creativity research today, and allow for everyday individuals' creative abilities to be measured, researchers have continued to question its application to real-world settings [2, 59].

Research on human creativity today draws not only from an acknowledgement of creativity as a deeply personal, introspective process but also as one experienced by all. Further, progress in research concerning the human creative process is evidenced in the increasingly creative methods researchers are relying on to study its origin by going beyond simple paper-and-pencil tasks or measures, and instead focusing on more context-relevant settings. For example, studies on creative performance have been conducted in dance through MoBI technology; while functional magnetic resonance imaging (fMRI) has been deployed to investigate creative writing in poetry composition and revision [60], action planning while imitating chord progressions comparing classical and jazz-trained pianists [61], musical improvisation using pitch sets or cue words in pianists [62], or semi-professional visual artists sketching drawing ideas for a book cover based on sets of descriptions [63].

Taken together, these studies make an important suggestion: creativity is likely to emerge from the interaction of multiple affective, cognitive and movement processes, and therefore the study of creativity should not be reduced to one measure or task. These studies, as reviewed in Sect. 4.3.2, are consistent with a model proposed in Liu et al. [60], showing inhibition of the dorsolateral prefrontal cortex (DLPFC) in the production of the creative product, increased cooperation between the DLPFC and ventromedial prefrontal cortex (VMPFC) during revision and evaluation of the work, and increased coupling between these two regions during the planning component of the activity.

4.3.2 Neuroscience of Creativity

We postulate that creativity lies in an individual's ability to produce a composition, object, artifact, sensory experience, actor thought that is novel, timely, with reward eliciting attributes (valued), and relevant within a socio-cultural context.

Although the exact neuroanatomical network that underlies creativity still remains unknown, recent neuroimaging studies have consistently implicated the prefrontal cortex(PFC) as an essential, fundamental structure involved in creative cognition, e.g., expressive movement execution and imagery as well as in many cognitive abilities such as processing complex information, abstract thinking, conceptual expansion and cognitive flexibility [64]. Thus, research suggests fundamental cognitive functions (integrating highly processed information, abstract thinking, cognitive flexibility, etc.) of the prefrontal cortex as central in forming the foundation for original thoughts from which a moment of creative insight can emerge. Further, these prefrontal functions can be understood as originating mainly from two regions within the prefrontal cortex: the VMPFC and DLPFC [60].

The VMPFC and DLPFC each represent one of two broader neural systems within the brain—the emotional (i.e., instinctive, visceral) system, and the computational (or cognitive) system, respectively. More specifically, the VMPFC, or the emotional system, is thought to draw from life events and assesses the emotional, personal content contained within them [65, 66, 67].

This emotional system attaches value to an experience by evaluating its relevance to an individual's life experience, memories, and training. This follows from the finding that the VMPFC is strongly connected to the limbic system, which regulates important functions such as emotion, motivation, the internalization of values/rewards, and the evaluation of the consequences of one's actions [68]. Moreover, research has shown that the DLPFC, or the computational system, receives sensory input from the TOP (temporal, occipital, and parietal lobes) as well as is involved in working memory and, consequently, cognitive flexibility—thought to be important components of the creative process.

Working memory not only produces temporary representations of the immediate, real-time events occurring around an individual, but also creates a buffer, which allows one to momentarily hold these representations, integrate incoming and past knowledge and stimuli that is relevant to solve a particular problem, and manipulate those stimuli to generate creative work. A review and meta-analysis performed by [69] examined the effects of two non-invasive brain Stimulation techniques: repetitive transcranial magnetic stimulation (rTMS) and transcranial direct current stimulation (tDCS) on the DLPFC as well as working memory performance, specifically through an n-back task[2]—a widely-used measure of working memory. Stimulation of the DLPFC resulted in faster and more accurate responses on this n-back task, suggesting that the DLPFC is heavily connected to working memory.

[2]The n-back task is a common measure of working memory capacity. In order to complete this

In addition to the significance of the prefrontal cortex for creative thinking, studies Have also implicated the parietal lobe as heavily connected to creative activity—both spatially and emotionally. Overall, parietal regions have been recognized as significant for body-environment interactions (specifically for "visual exploration," motor use of the hands, and tool use). Recent research also supports the importance of the parietal region in higher-order processes such as multisensory and sensorimotor assimilation, spatial orientation, motivation and intention, and the representation of the external environment's relationship to the body [70, 71]. Further, research has also cited the contributions of the parietal lobe as extending to cognitive functions such as episodic memory retrieval—consciously accessible memory for specific events that allow humans to retrieve past experiences and employ them for future goals. A literature survey performed by Wagner et al. [72] revealed that fMRI as well as EEG studies on episodic retrieval have highlighted significant activity in the temporal and lateral posterior parietal cortex. These tools, including visual exploration, motor capabilities, tool use, spatial orientation, motivation, and memory retrieval, amongst others are central to the creative process of generating art.

4.3.3 Uncovering a Neural Signature for Creativity

Within the highly interconnected functional brain networks, and based in the consistent findings summarized in Sect. 4.3.1, we hypothesize that there is a cortical neural signature that emerges in the brain during aesthetic experiences,both during production and contemplation of a work of art. To study this potential electrophysiological neural signature, we propose an innovative experimental protocol to study the human creative process in authentic experiences.

The investigation of this hypothesis has the potential to provide a unifying view

task, subjects are presented with a series of stimuli (such as numbers or letters), and are asked to identify when a given stimulus corresponds to one seen n number of steps earlier.

that informs traditional art theory and art practice. The neural signature associated with creative output would be likely expressed in distinct, distributed, and temporally evolving cortical activation patterns that can be measured with MoBI technology and characterized with functional connectivity and neural decoding analyses (see, for example, [20]). We also expect that such brain patterns tagged to creative output may show neural individuality and variance across participants and art forms modulated by situational context, skill level, demographics and other factors yet unknown.

Uncovering a neural signature for creativity would likely lead to new metrics or biomarkers associated with the creative process, which could guide potential interventions for acquiring and tracking the development of new creative skills, and evaluating art therapies [73]. Critically, such a model ought to integrate links to existing art theory, art practice, and art therapy. From the detailed understanding of the neural mechanisms of human creative expression, we can develop BCIs for artistic or therapeutic purposes that interact adequately with the user input (Fig. 4.1).

4.4 The Exquisite Corpse as an Experimental Protocol to Study Creativity in Action and in Context

We propose a transdisciplinary and multimodal experimental approach to study the human creative process using MoBI technology. This approach is based on four principles set forth for an effective transdisciplinary collaboration. First, transdisciplinarity between fields requires the convergence and synthesis of different research methods. This convergent research requires equal input from scientists and artists on

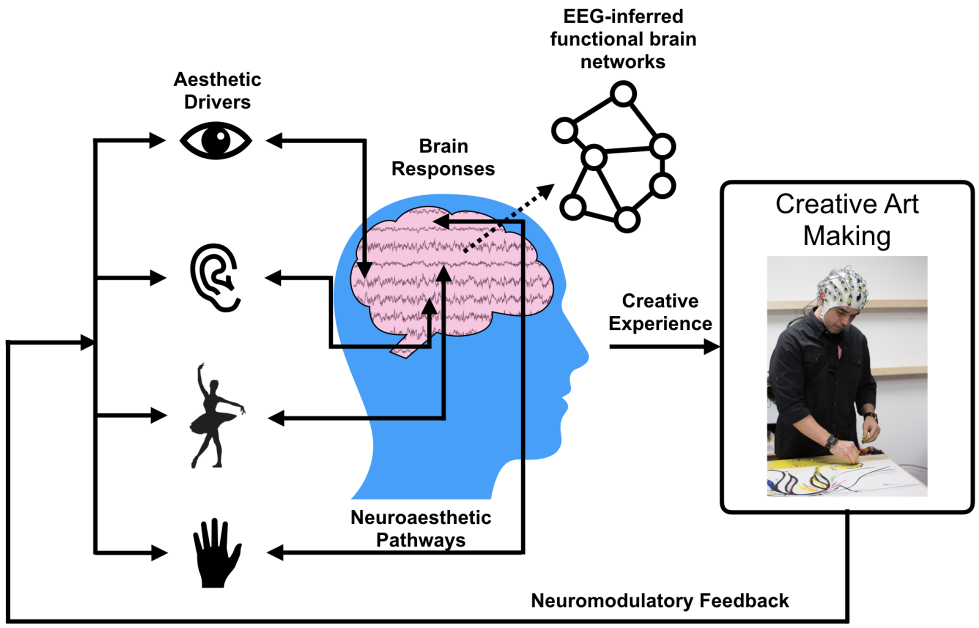

Figure 4.1: MoBI technology enables the study of the human creative process in freely behaving individuals performing in complex, natural, and authentic settings.

experimental design to the interpretation and applicability of the data. In this case, bridging a data-driven bottom-up approach with top-down analysis from the artist's perspective and first principles will be crucial to investigate the creative process. Second, we considered an experimental protocol that would allow for the inquiry into common and unique neural patterns of brain activity across artistic domains and individuals. We therefore need an experimental protocol that can be implemented across different creative categories (e.g. visual, dance, writing, etc.), people of different skill level (e.g. novices, experts, children, adults), and demographic factors including age, gender, language, geographical location, etc. Third, to create an authentic creative experience—and to explore the meaning of "authenticity" across artistic and scientific domains—we envisioned an experimental protocol that would allow for data collection from freely behaving individuals in a real world setting. A fourth criterion was that of practicality and scalability. We sought an experimental protocol that would allow to produce a work of creative expression within a reasonable amount of time that would be accessible to experts and novices, been enjoyable for the eventual participation of spontaneous in situ participant volunteers from the general public (e.g. children patrons at the Children's Museum of Houston), with the potential for scalability, and a common framework from which to extend into other artistic domains.

The effort to define a protocol that fit into the criteria described above resulted in the re-contextualization of the Exquisite Corpse as a MoBI-enabled neuroscience protocol from which to study the human creative process during creative improvisation. The protocol is defined in the spirit of the Exquisite Corpse, a game invented by the Surrealists in the 1920s that consists of building a three-part improvisational piece from the contributions of different players [74]. In the growing field of neuroaesthetics, it has become fashionable to make the claim that artists were our first neuroscientists. Studying painters of the past, for example, offers insight into how artists illuminated brain structure and the mechanisms of perception through inventive techniques of luminosity, rendering of shadows, and an understanding of the visual illusions our brain plays on perception [75]. Less explored is an analogous argument: the rich tradition of artist's inventive performances,games, "actions," or "prompts" holds similar insights for the brain sciences today. By adapting the Exquisite Corpse, which incorporates improvisation, collaboration, and novel problem solving as experiment design, we can merge the long tradition of the arts exploring the inner workings of the mind with a replicable scientific protocol.

4.4.1 History of the Exquisite Corpse

First gaining popularity in the 1920s, Cadavre Exquis, or Exquisite Corpse, was originally conceived as a word-based parlor game relying on collaboration, chance, and unexpected juxtaposition. The game typically involved three to four players who would each secretly write a word or phrase on a shared piece of paper, then fold and pass the sheet to the next player. When opened to reveal all sections, this process often produced nonsensical phrases like “Le cadavre exquis boira le vin nouveau” (“The exquisite corpse will drink the new wine”), wherein the game obtained its name. The game was soon expanded to visual imagery through drawing and collage, where the players would attempt to create a “body” consisting of head and shoulders, torso and arms, legs and feet. In this version, players are allowed to see the edge of the previous composition to begin their own. Other art forms such as dance, music, and poetry have also adapted the game for their respective genres.

Around 1925, members of the artistic movement known as Surrealism began to explore the game’s possibilities within the arts. Seeking ways to break freely of what they considered the limitations of the rational mind, and rejecting the 19th c. approach to purely representational and observational painting, the Surrealists were deeply invested in exploring ways to disrupt the conscious mind’s need for order.

They were drawn to the elements of chance, randomness, and unpredictability that the game produced and believed that this revealed a more authentic view into the creative subconscious mind. As the founder of the Surrealist movement, André Breton, stated, “With the Exquisite Corpse we had at our disposal—at last—an infallible means of sending the mind’s critical mechanism away on vacation and fully releasing its metaphorical potentialities [74].”

4.5 Recording MoBI Data in the Exquisite Corpse Protocol

The human creative process is a multi-dimensional and multi-stage process that does not happen in isolation; rather, it is fueled by environmental stimuli [76, 77]. The protocols outlined below attempt to capture the creative production process as it happens in freely behaving participants, involving elements of social interaction and environmental and other contextual factors occurring in a real-life scenario.

4.5.1 Instrumentation

In this protocol, brain activity is typically collected with 64 active-electrode wireless EEG sampled at 1000 Hz (e.g., BrainAmpDC with actiCAP, Brain Products GmbH; see [22] for examples of MoBI headsets);eventually downsampled to 200 Hz.

Four electrodes are used for EOG recordings. IMUs are used to track head and body motion data from the artists that capture the creative gestures of the performers, while providing useful information for identifying potential motion artifacts. Typically, for the visual artists, musicians and writers, data are collected from the head and forearms. In the case of the dancers, six IMUs are placed on the head, both wrists, torso, and both ankles of the dancers. Video cameras capture the creation of each work of art and the group dynamics. After the experiment, the artists are asked to annotate the video recordings to mark significant behavioral and cognitive events they recall. Annotators during the performance also provide event tagging, which is complemented by regions of interest identified from other sensor data (e.g., arousal from electrodermal activity). An example of a typical experimental setup with sample EEG, acceleration, and video data is shown in Fig. 4.2.

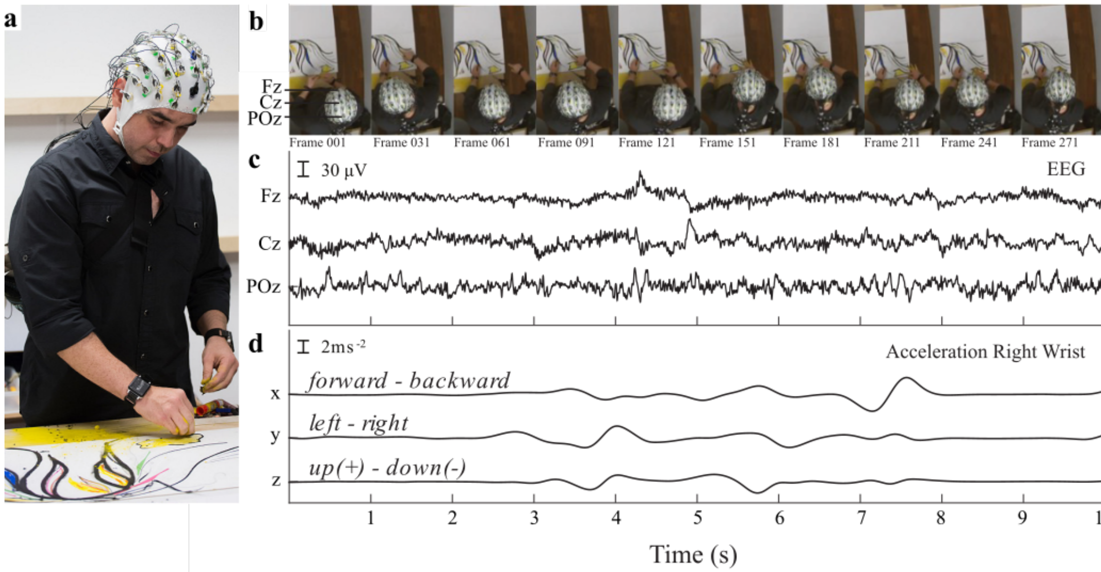

Figure 4.2: Experimental setup for the Exquisite Corpse in the visual arts. a) An artist wearing mobile EEG and IMUs. b) Video recording. c) EEG from three electrodes. d) Tri-axial acceleration from right arm.

4.5.2 The Exquisite Corpse as an Experimental Protocol

The Exquisite Corpse protocol includes baseline and experimental conditions, with the baseline conditions, with the Baseline conditions introduced before and after the experimental session and consisting of closing eyes for at least 60s, and looking at a blank sheet of paper for at least 60s. The experimental conditions are detailed below.

Visual Arts

In the visual arts modality of the Exquisite Corpse, three artists typically work on a “body” consisting of three sections: head, torso, and tail/legs. The artists are provided with a foldable triboard (32 in x 40 in four-ply chipboard), a2-layered panel comprised of three sections that can be folded or ‘blinded’. At the end of each section, the staff covered the art piece with a strip of cardboard, leaving approximately 3 cm uncovered at the bottom, and then transported the piece for the next artist to view before beginning the next stage. The artists worked on the three art pieces simultaneously, on three different triboards. The artists are separated from each other by opaque curtains to prevent interactions during the experiment.

The artists were asked to provide or identify basic art materials such as pencils, pastels, chalk, charcoal, water-based painting materials, glue, and scissors for use during the performance. Artists are also requested to bring "surprise" materials for one another as a way to bring an element of surprise as well as personalize—and construct meaning through—the process. Examples of materials brought by the artists include insects, stickers, ink, film, stencils, and printed color paper.

Fig. 4.3 shows the experimental setup and timed protocol. The artists (labeled S1, S2, S3) work on separate boards (A, B, C) on the head (Section 1) of the figure for 15 min. The boards are rotated, and the artists continue to work on the body for 15 min (Section 2), and subsequently the tail/legs for the last 15 min (Section 3).

Versions of this protocol for children typically limit the duration for each session to 5 min given time limitations and attention span of the children (Fig. 4.4).

Creative Writing

In this instantiation of the Exquisite Corpse, three creative writers work simultaneously on three compositions (which can include poetry and/or prose).The writers start by writing on a blank notebook, and for each consecutive session, they continued from where their collaborators finished their writing at the end of each session. The writers are able to see the last two lines of the previous text. The sections are 15min long with 1 min vocal warnings before the end of each. Three Exquisite Corpse texts (A,B,C) are produced at the end of the 45 min experiment (Fig. 4.5).

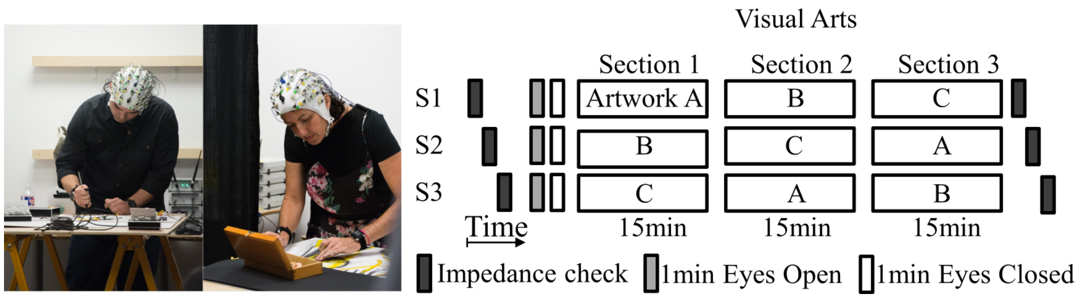

Figure 4.3: (Left) Three artists (two pictured) worked simultaneously creating the head, torso, and tail/legs of a figure in the spirit of the Exquisite Corpse. (Right) Experimental protocol design.

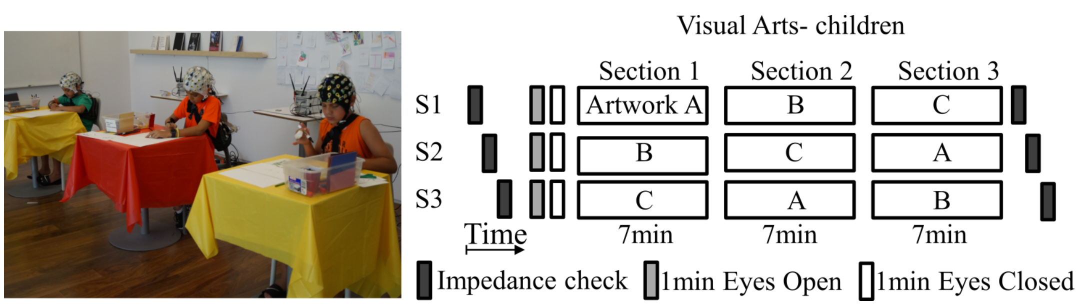

Figure 4.4: Three children participating in the Exquisite Corpse protocol for the visual arts.

Music

In the musical adaptation of the Exquisite Corpse, three musicians work on three improvisational jazz pieces, each divided into three sections. In the first section, one musician plays while the others listen. For the second section, a second musician joins in for a duet, while the other listens. The last musician joins the others for the last section. Each of the sections was 5 min long. A timer is placed visible to the musicians so that the subsequent musician joined at the 5 min mark. The process is repeated three times, rotating the order for the musicians. The musicians' performance sequence is represented in Fig. 4.6.

Dance

The dance adaption of the Exquisite Corpse involves three dancers separated by curtains so that they could not see each other during their performance. In the first section, the dancers performed in silence, dancing with external cues or music. The second section of the Exquisite Corpse features a 144 bpm Alegría (with cajón and palmas) flamenco metronome [78]. The third section features an instrumental musical piece: Raff's Ode au printemps in G major Op.76 200. The songs were edited to the length of the section (10 min) prior to the experiment.

Each dancer performed improvisational movement for 10 min in isolated stages. The first section was followed by a 1 min collaborative performance where they stepped into view of each other and shared movements among them. They then returned to their isolated stages for 9 min, and repeated this procedure for the third section of the experiment. Fig. 4.7 summarizes the protocol followed. The sections were10 min long with a 1 min vocal warning.

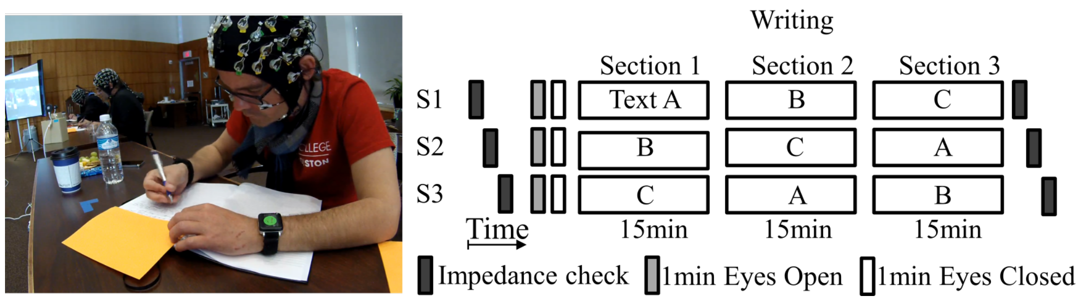

Figure 4.5: (Left) Three artists worked simultaneously creating the beginning, middle, and end of a creative writing piece in the spirit of the Exquisite Corpse. (Right) Experimental protocol design.

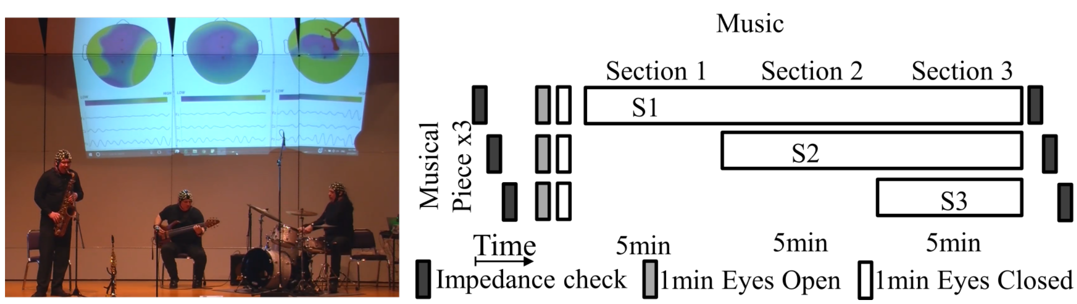

Figure 4.6: (Left) Three musicians participate in the study, playing a five-piece drumset, and bass, and a saxophone. (Right) Experimental protocol for improvisational music performance.

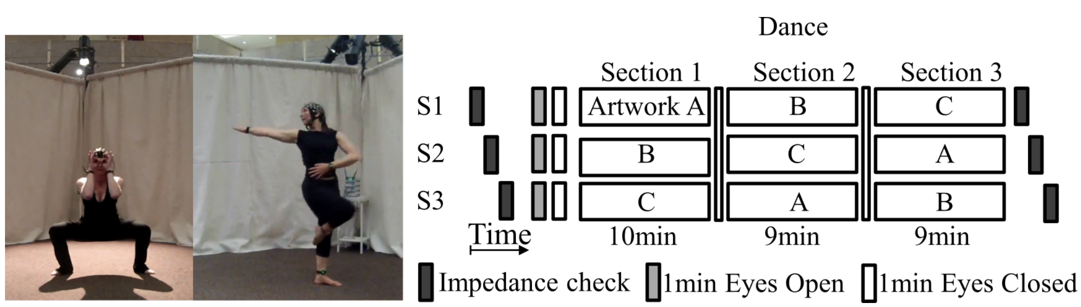

Figure 4.7: Three dancers (two pictured) participated in the study. (Right) Experimental protocol for the dance version of the Exquisite Corpse.

4.6 MoBI Data Analysis Through Machine Learning

We present, as an example of an analytic methodology, the data processing for one participant in the Exquisite Corpse for visual artists. The machine learning methodology proposed requires label actions from the artists, with labels relevant to the artistic modality, and a classification approach with automatic feature extraction and visualization.

Data driven neuroscience studies have found great success in applying supervised and unsupervised machine learning techniques to find relationships between the data collected and a behavioral response observed. Classical machine learning requires the researcher to identify, obtain, and select features of the data to analyze.

In EEG, these features usually take the form of power in commonly used frequency bands: e.g. delta 1–4 Hz, theta 4–8 Hz, alpha 8–12 Hz, beta 12–30 Hz, gamma 30–50 Hz; or time domain features involving temporal and spatial relationships in the data. These features are used decode movement intent in mobile settings [17, 18, 19, 33, 79, 80]. Coherence metrics, which measure the functional connectivity between electrodes, have also shown to be promising features for EEG analysis [81]. Quantitative neuroscience based on EEG has developed through a combination of spectral, temporal, and spatial features, with which researchers are able to build a set of descriptors to feed into machine learning algorithms to learn about the data and to build models for intentionality prediction [23]. Classical machine learning techniques in neuroscience involve a combination of features selected by the researcher, based on previous neuroscience or a promising new metric. The features are tracked and averaged over hundreds of trials to find an overall pattern of brain activity that can be associated to a specific task.

In order to study the neural basis of a complex cognitive task such as the human creative process across demographics and artistic domains, we find that automatic feature extraction algorithms offer a promising new approach to find new data descriptors and predictors. Automatic feature selection algorithms have shown rapid progress in recent years, in particular in the field of machine vision, which have also been applied to EEG data [50]. Promising automatic feature extraction algorithms include those based on deep neural network architectures such as convolutional neural networks (CNNs), long-short term memory networks, Boltzmann Machines, or a tactful combination of these.

Feature visualization remains a key aspect of automated feature extraction methods. Hypotheses and feature visualization techniques based on previous neuroscience (e.g. we expect alpha power changes in prefrontal cortex; is that what the computer finds?) help the researcher understand if the algorithm is learning useful and relevant information. Therefore, it is necessary to have a top-down, artist-informed framework from which to base the feature visualization methods and overall data analysis when using automatic feature extraction methods. Data mining techniques, however sophisticated, will fall blind to the task and rendered ineffective, even counterproductive, to the field if they are not accompanied by appropriate feature visualization methods.

The proposed machine learning method described below requires labeled datasets. We annotated the data by having human annotators watch the video recording of the artists as they worked on their composition. Because the experiment is unconstrained by design, there are two critical aspects to consider in this approach: (1) what classes to label the artists' actions into, and (2) inter-annotator consistency. Relevant labels were discussed and analyzed with the professional artists that participated as subjects in our study through interviews.

4.6.1 Labeling Creative Tasks

The Exquisite Corpse protocol in the visual arts consisted of elements from drawing and collage. The video recordings were visually segmented by annotating the behaviors and tasks done by the artists, relevant to drawing and collage. A second person validated the annotations.

The MoBI data were segmented in terms of the artistic action each artist displayed: planning/observing, cutting, placing/pasting, correction, outlining, tracing, coloring, spreading, drawing, and writing. In addition, the baseline eyes open and baseline eyes closed were also segmented. In this example, four classes were selected for illustration purposes: baseline eyes closed, baseline eyes open, planning, and coloring.

4.6.2 Automatic Feature Extraction and Classification

In an unconstrained behavioral task, where artists work with elements of chance and improvisation to create a composition, we consider that a machine learning approach with automatic feature extraction would enable us to capture neural dynamics and processes that are hard to predict a priori (e.g. by having the researcher select what features to analyze).

CNNs have shown impressive results in the field of machine vision due to their capacity to learn local patterns in data through convolutions. With the proper architecture, CNNs can find important features of the data automatically, potentially opening the possibility for discovery of previously unknown relevant features. These networks are built by adding convolutional layers that map local patterns in the data. CNNs make good candidates for end-to-end decoding: from raw EEG data to a prediction about behavioral intent. However, they require a large number of hyper-parameters, so they also require a large amount of training data and representative variations in that data. They also take along time to train compared to simpler models often used in neuroscience studies.

We used a CNN for automatic feature extraction and classification of the creative tasks. Fig. 4.8 shows the CNN architecture selected for the study. Our architecture parameters were selected based on the discussion in Schirrmeister et al. [50], fine tuning them to our data. Deep learning approaches require a large amount of data to iterate over, in which by means of backpropagation, the weights of the computation units in each layer are updated such that the metric of interest (mean-squared error before the Softmax layer) is minimized. The EEG data was augmented by taking 1 s time windows with 99% overlap. The first temporal 80% of the data was used for training and validation, while the latest temporal 20% of the data per class was used as the test set. This partition enables the learned model to be tested in pseudo real-time data: the test set. To build the classification model, each of the four classes were set to contain 5000 samples using random sub-sampling without repetition for the training and validation sets. From the 20,000 samples, 13,000 were selected for the training set and 7000 for the validation set. The network ran 10 times to compute a distribution of the classification accuracies, with randomized selection of the samples to be used for the training and the validation sets. 4000 samples were selected for the test set, with 1000 samples per class.

To illustrate the performance of the CNN on our 4-classes problem, the CNN was tested on artist one (S1). The accuracy for the training and validation sets reached near 80–90% in both cases, with classification accuracy dropping to near 66.5% in the test set (Fig. 4.9). The classification accuracy in the CNN improved after utilizing the temporal properties of EEG: there is a higher probability that the classification for sample x is similar to the classification of the temporally adjacent sample. In this

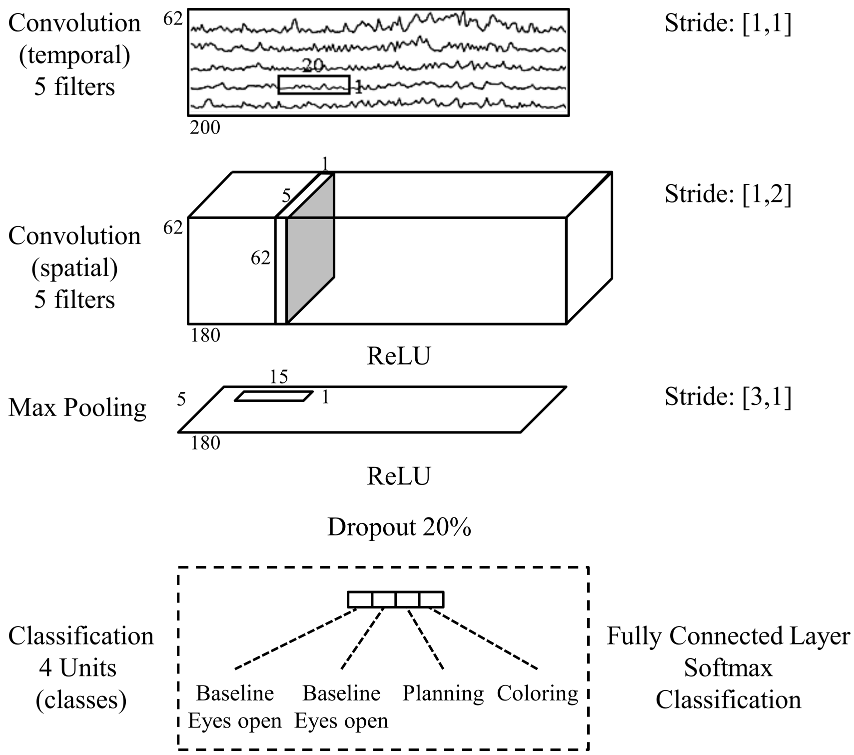

Figure 4.8: CNN architecture proposed. The EEG inputs are windows of 62 channels by 200 time samples (1 s, at 200 Hz).

application, our tied-weights consisted of averaging the classification output (before Softmax) of the immediately previous 5 samples before running the network through the Softmax layer and finally selecting a class label for the sample.

4.6.3 Feature Visualization

In neuroscience, we are interested in understanding the neural features that contribute to the classification of tasks. In this unconstrained experimental setting with multiple and varied actions performed by the artists, these features may be a combination of several different cognitive processes acting together. Therefore, visualizing the features learned automatically is critical for understanding the performance of the classifier, and thereby the relevant feature spaces associated with the task.

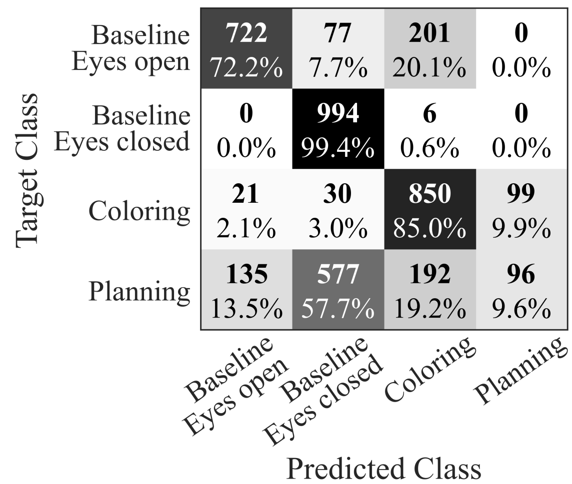

Figure 4.9: Confusion matrix for EEG data classification of artist 1. Each row contains 1000 test set samples per class.

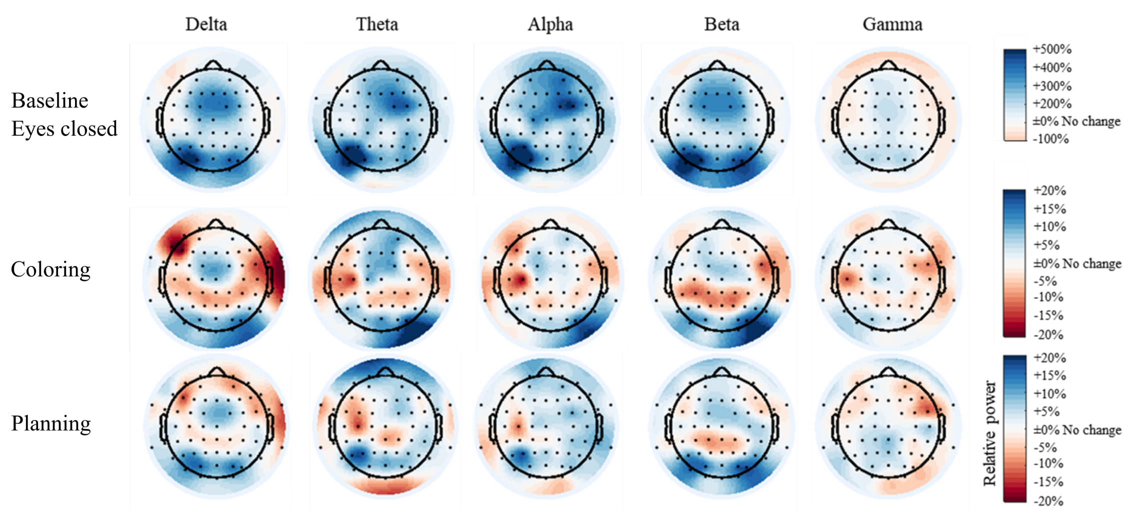

Figure 4.10: EEG feature visualization, as learned by the CNN: spectral differences in the best examples from each class. The colorbars show the percentage spectral power change with respect to ‘Baseline with Eyes Open’.

A method used to identify the most relevant features for the network was to find the best examples (highest activation in the last layer before Softmax) for each class and compare the spectral differences between them. Figure 4.10 displays the results of the spectral power in the 200 best examples from each class: those which yielded the highest activation in the last layer before the Softmax for each class and therefore those which the network found to be most representative of each class. The spectral power in each class was compared to "Baseline Eyes Open". In this visualization method, there is an increase in power in the occipital area expected for "Baseline Eyes Closed" (Fig. 4.10). There is a decrease in power in the theta and alpha power in left central scalp areas for the "Coloring" and "Planning" tasks: the artist worked with their right hand. An increase in delta, theta, and alpha bands in left-parietal regions is found for the "Planning" task. Although these observations are for one subject at the sensor level and they not necessarily reflect the cortical sources of brain activity, the method shows promise for understanding the neural features and channel locations that the network found to be most relevant for classification.

4.6.4 Top-Down Analysis of the Creative Process

A top-down analysis, using insights from the experts in the creative compositions —the artists themselves, was used to interpret the feature visualization and feature relevance results. The corresponding interviews of the artists were conducted the day after the experiment. The video recording of the experiment was shown to each artist and their recollection of their process was recorded.

The feature visualization techniques showed importance of scalp areas over the frontal and left motor regions during the execution task in the delta and alpha bands. Parietal and frontal scalp areas were relevant in the planning tasks, in the theta and beta frequency bands (Fig. 4.10). Artist one (S1) not only utilized many different colored pastels, but also incorporated small film strips, pieces of paper, felt, and carefully rolled strips of tape and stickers into the artwork (Fig. 4.11). Each of these tasks—coloring, aligning strips of film, cutting and placing paper and felt, and rolling and positioning tape—are largely spatially dependent as well as involve careful planning and attention to detail, and thus, involve the parietal and frontal areas.

With further source analysis, we hypothesize that we would find involvement of the VMPFC in the artists. Research identifies the VMPFC as heavily connected with the limbic system, which regulates emotion, instinct, motivation, and the internalization of values, and these personal and meaningful emotions, reflections, and beliefs of the artists are clearly manifested through their expressive and telling work.

Both artists two (Fig. 4.12) and three (Fig. 4.13) reported to have felt a "real connection to each other and the space" around them, which they described, "allowed them to give into someone else's sensibilities." Additionally, each of the two artists reflected on their work and mentality during their moments of creation, citing that they each thought more about themselves rather than the state of others. Artist three created a powerful message— "How Can I Resist?"—that was central to her artwork and influenced by thoughts she had earlier that day, reported to have felt a sense of "authenticity, familiarity, and relief" while creating her work as well as remembered that she had "less moments of reflection" during her creative process itself—intimating that the process was more intuition-driven, an important feature of the VMPFC.

Moreover, these artists incorporated additional materials in their artwork, such as paper, dead butterflies, plastic eyes, and tape, as well as utilized coloring, and placing paper, amongst others, pointing to the parietal activity that was seen in the feature selection data. This raw, unfiltered integration of external and internal

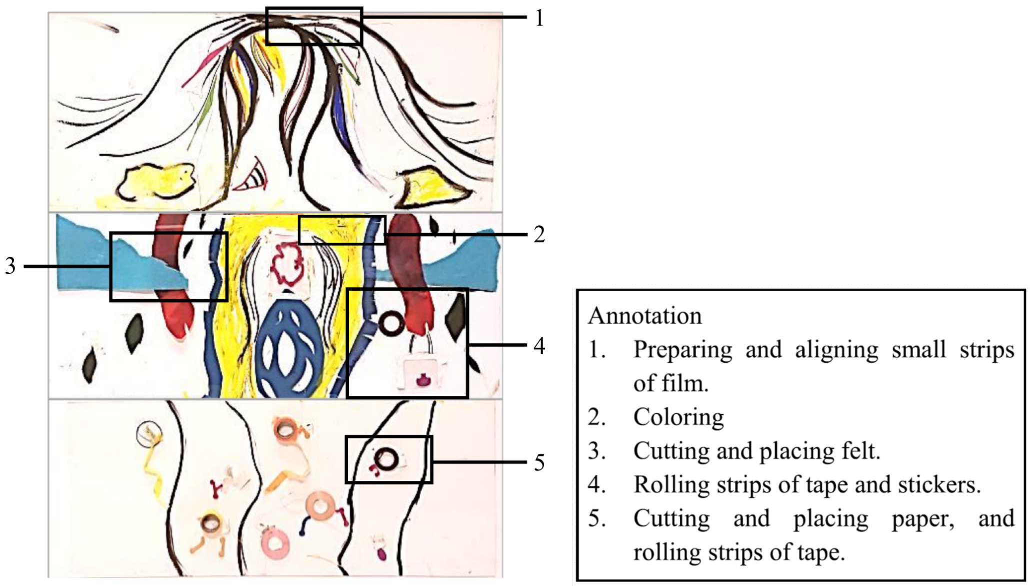

Figure 4.11: Artwork created by artist one (S1), with annotations. Inset Examples of annotated tasks performed by the artists.

stimuli present in the works of each of the artists not only motivated the production of novel arrangements of ideas, experiences, and sensory inputs, but also facilitated the transition of these arrangements into a meaningful, creative work (Figs. 4.11, 4.12, and 4.13).

4.6.5 MoBI Data Analysis Across Artistic Modalities

A similar data analysis pipeline, as described in this section, can be applied for other artistic modalities. The data can be labeled from a discipline-specific annotation framework. For example, in dance, where research typically involves studying expressive movements, a labeling system based on Laban Movement Analysis provides the appropriate tags for the MoBI data; see, for example [19]. A CNN, with parameter fine-tuning, could be implemented for automatic feature extraction for the set of labels defined, and a similar feature visualization approach would be useful to

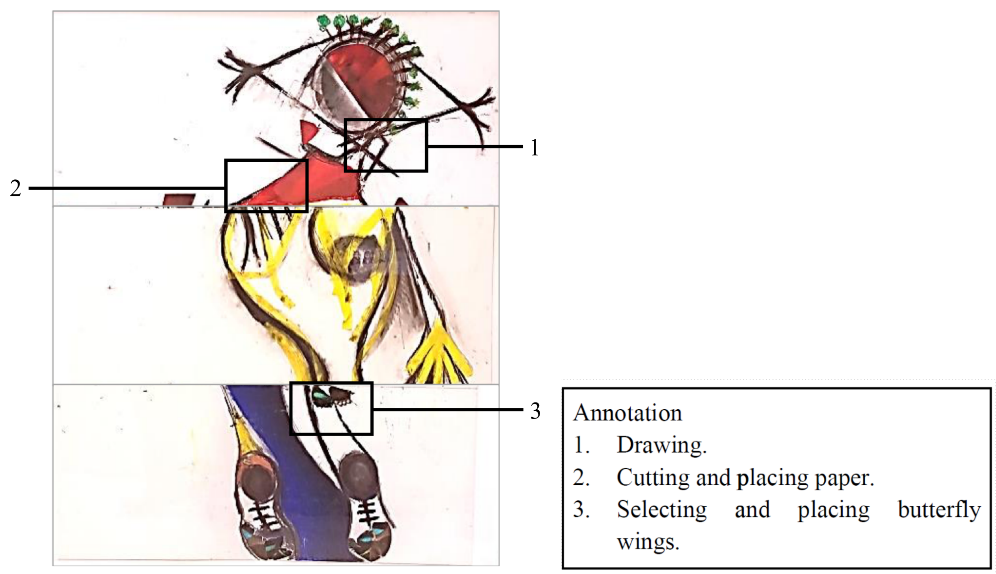

Figure 4.12: Artwork created by artist two (S2), with annotations.

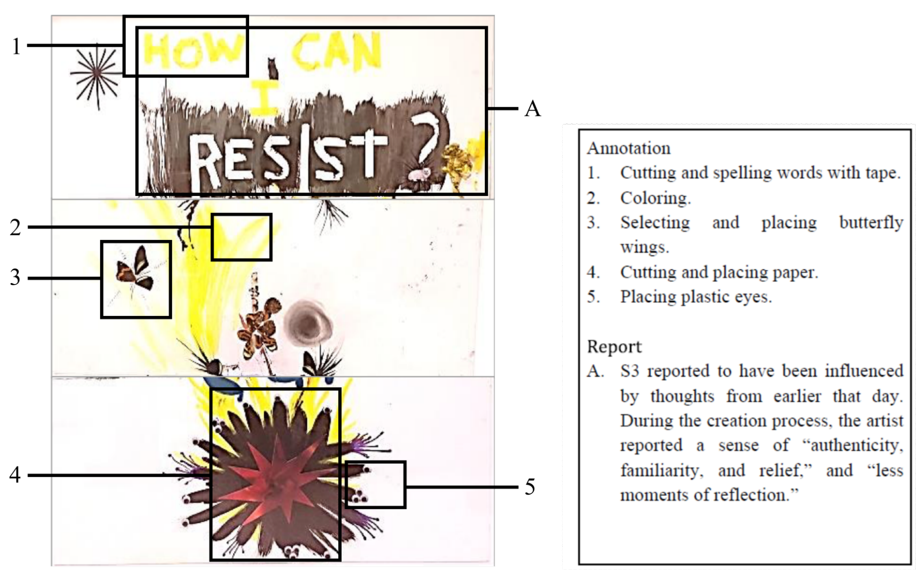

Figure 4.13: Artwork created by artist three (S3), with annotations and an example of a report provided by one of the artists.

understand the features being learned by the computer.

Classical machine learning approaches with predefined and well-known EEG features offer performance baseline and comparisons for the automatic feature extraction algorithms. See [23] for a review of machine learning algorithms often used for EEG-based BCI applications.

4.7 Discussion: On the Question of Authenticity

The burgeoning field of neuroaesthetics, of which our proposed protocol falls under, is an excellent example of the necessity of transdisciplinary problem-solving. A mystery as complex as human creativity cannot only be understood through a single approach and requires the synthesis of expertise from multiple disciplines. While creativity and aesthetic experience undoubtedly have a physical, neurological under pinning, this should not be misunderstood as an "explanation" of art, but rather a characterization of the creative process. A rigorous neuroaesthetics needs to account for the lived, emotional and experiential aspects of art, as well as its ability to construct and represent values and meaning for the individual and society. This is why neuroaesthetics represents a rare instance wherein the advancement of a scientific field hinges on meaningful interactions with the arts. This interaction should not only be with art of the past, but with living artists and contemporary institutions of art such as museums, galleries and artist's studios. The Exquisite Corpse experiment was designed to address this issue of collaboration with contemporary artists while producing valuable data for both the scientist and artist.

From the artists' point of view, not only is it an unusual experience to be in the role of test subject, but it offers a novel lens through which to reflect on their creative process. In our proposed approach to study creativity, research required each artist to examine their own creative practice in order to better articulate processes and parse specific moments, while learning about how creativity is perceived within the parameters of neuroscience. The artists found that their self-reflections offered them a more nuanced understanding of their own creative process and how it was in tension with the scientific assumptions of it, either through working definitions of creativity and aesthetics, experiment design, expectations about the end results, or even the post-experiment evaluative process. This intersection of artistic reflection and neuroscientific discovery is of great importance as we build a common language with the hope of advancing each of our respective fields in unexpected ways.

Although many questions were provoked, a recurring theme appeared to anchor them, which can add valuable insight and inform the development of future experiments: What does authenticity mean in relation to creative processes, and how do we measure it? Like "aesthetics" or "creativity," the concept of "authenticity" from both the creator and observer's points of view, has a complex meaning that is usually understood as highly personal and subjective. But, in the context of these studies, there is an expectation between artist and scientist for a common definition and, perhaps most problematic for the artist, a quantifiable categorization of authentic creativity.

The question of authenticity is particularly relevant in light of major advancements in MoBI technology: the ability to record real-time data from a diverse group of freely behaving individuals makes it possible to study creativity outside of highly controlled and artificial laboratory settings. The assumption is that a typical site of artist production, such as a studio or museum, will facilitate a more authentic experience and, hence, the resultant scientific reading will be more accurate than data gathered in a traditional laboratory setting.

But if the innovation of this technology partly hinges on more accurate, i.e.

"authentic," recordings, then the artist's understanding of authenticity as it relates to creativity must be given an equal consideration in the experiment design and the evaluative process. Because even though we have moved this experimental procedure away from the laboratory setting, the situation presents a new set of highly artificial variables that could disrupt the artist's sense of an authentic experience.

Additionally, breaking down the constituent physical and measurable aspects of the creative act (e.g., stroke, cut, pasting, coloring, drawing, planning, etc.) has been an enlightening process for both artist and scientist. In the process, preconceived definitions of creativity (at least on a process level) must be challenged from the viewpoint of each discipline. Through the continued development of language and systems with which to articulate and report the experiences recorded in collected data, we hope to contribute to this technology's potential therapeutic goals, as well as investigate the rich artistic and philosophical questions posed by neurological understandings of creativity and aesthetics.

4.8 Applications

Creativity is not only integral to the actions and decisions of many individuals throughout their lives, but has also served as the foundation for bringing about substantial change and advancement within a wide variety of fields, including those of education, politics, economics, science, medicine, technology, and art. The human quality of creative abstraction has been championed by politicians, leaders, and educators alike as the answer to many of a nation's pressing issues [82]; as a method of teaching as well as a quality to cultivate within the education system [83] as a path to improving the products and services offered by corporations and institutions [84]; and as a means to aid individuals on their journey of personal growth and healing [85]. In the next two sections, we describe applications and potential impact of studies on the neural basis of creativity.

4.8.1 Creative Art Therapy for Neuro-rehabilitation

Creative art therapy allows an individual to articulate personal sensory experiences through the various visual and tactile properties of tools such as paints, pencils, stickers, charcoal, and stamps—for example—and the muscle pressure an individual must exert in order to manipulate these raw materials to form something meaningful [86, 87]. Further, it has been commonly found to be associated with numerous positive outcomes such as decreased stress [88], depression [89], fatigue [89], anxiety [90], PTSD [91], improvements in behavioral functioning, mood [92], speech [93], self-image, self-esteem [94], communication, responsiveness, and sociability [95], amongst others. As a result, art therapy has improved the quality of life of many individuals from various walks of life and backgrounds—including not only those inflicted by Alzheimer's and other forms of dementia [96], but also of those facing the daily stresses of life.

These studies highlight the effectiveness and potential of art therapy and provoke further questions that can only be answered through the neuroscientific study of the human brain in artistic production in real world settings: How can medical professionals, therapists and neuroscientists collaborate more effectively with artists to personalize creative art therapies as a form of precision medicine? Empirical neuroscientific data from collected in mobile settings during the process of creating a work of art offers the possibility to create better, more effective, personalized therapeutic interventions. By analyzing the neural dynamics associated to the human creative process, art therapy methods can be personalized for optimal performance.

Figure 4.14: An interactive artistic BCI that uses selective neural features to control the sculpture's position, color, and sound. A dancer, Shu Kinouchi, interacts with the space in real time. Photo by Ronald L. Jones.

4.8.2 Artistic Brain-Computer Interfaces (BCIs)

Understanding the neural basis of creativity has the potential to develop artistic BCIs that can promote creativity in art making and also provide alternative ways of visualizing brain data. The chapter by Todd et al. [97] is an example of how EEG activity can be used to represent and visualize multiple aspects of brain activity through motion, lights and sound (Fig. 4.14). Closed loop artistic BCIs can also be deployed as powerful neuromodulators of brain activity to augment the repertoire of the artist by allowing brain control of the environment or stage.

4.9 Acknowledgements

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4.10 Author Contributions Statement

JGCG collected the data (with help from the staff and students from the Laboratory for Noninvasive Brain-Machine Interface Systems), performed the data analysis, and wrote the first draft of the manuscript. GC contributed with the top-down analysis, literature review, and applications. JGCG, DR, and JLCV designed the experiments. DR and JLCV conceived the research. All authors wrote the manuscript. All authors reviewed the manuscript.

Chapter 5

Embodied writing: EEG in Real-World Creative Writing Workshops. Experiment Design and Rationale

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5.1 Abstract

The process of creative writing does not happen in isolation; rather it happens through the experience of the body in the community we live in, which frames organically the written word within the community that contains it. Mobile EEG provides the opportunity to study an authentic creative writing experience of writing as a

[1]To be submitted as a journal article in 2019-2020. The chapter organization is based on the template from the Journal of Writing Research.

community.

The two studies described here are the first neuroscience experiments to study real-world creative writing. The workshops integrated mobile EEG to explore the neural basis of the creative writing process in bilingual students: from skill development to the embodiment of the process, making drafts, discussing them, and editing a published book as a final product. Two workshops were instrumented with mobile EEG: one with EEG collected during the preparation and production stages, and one with EEG recorded pre-workshop, post-workshop, and within two peer text discussion sessions.

5.2 Introduction

Creative writing involves embodied practices that physically connect us with our surroundings, our community, and our bodies' interaction with them. To study the neural basis associated with the creative writing experience, we propose to measure brain activity as students in a creative writing workshop walk through the city of Houston, prepare drafts, workshop their texts, and produce texts regarding specific locations and communities visited during the workshop. The process of creative writing does not happen in isolation in a closed-room space, rather it happens in the street, in the sidewalk, at the park, at the cemetery; at any space of social interaction that frames organically the written word within the community that contains it [98]. Mobile EEG provides the opportunity to study an authentic creative writing experience of writing as a community.

EEG systems have traditionally shown to collect high-quality brain activity data that has been used to study a wide spectrum of neuroscience questions, from basic neuroscience to the interaction of brain and machine with BCIs with a high degree of accuracy and temporal resolution [17, 18, 33]. The development of reliable, portable dry-electrode systems has reduced setup time and made possible experimentation in public venues [35, 22, 20, 54] and in unconstrained environments [1, 21]. MoBI technology is currently the only brain activity recording technology that allows for repeatedly testing behavioral paradigms [99], with all the relevant cognitive and functional tasks associated with them, as they occur in contextually rich and relevant situations.

5.3 Neuroscience Background and Hypotheses

In previous EEG studies pertaining to creative writing, highly creative individuals exhibited higher alpha indices during a creative inspiration (preparation) than creative elaboration (generation); which was not found in less creative subjects [100]. As subjects thought about writing an essay, more creative individuals (based on "creativity scores" from Torrance tests) showed higher coherence across the scalp, in the alpha band [101]. Alpha power in frontal, central, and parietal locations has been consistently found to be modulated in relation to creative task demands, to increase in relation to an individual's creative level, and to increase after performing a cognitive creative problem solving task [14].

Erhard [102] and Liu [60] have proposed working models for the human creative process based mainly on neuroscience done in laboratory settings and fMRI studies. They found DPFC deactivation during creative production, and activation during text revision. These provide valuable insight into the nature of the human creative process, but they leave the question of authenticity unresolved as the experimental setting is carried out inside an MRI machine, far from natural contextual and free-motion settings in which individuals usually create. Fink [14] discusses the role of alpha power in creative ideation measured with EEG.

We hypothesize that there will be task-related modulation of neural activity in lateral and frontal areas of the scalp, from the preparation phases to the production phase; and that mobile EEG provides the means to record these changes in authentic settings.

We expect that as the students' creative writing skill develops, the features related to the creative writing process will be accentuated in the after-intervention session. Central and parietal areas would become involved from the use of memory (after interacting with the locations used as stimulus), spatial planning for their compositions, and increased involvement in theta band with periodic modulation (spatial navigation and recollection) [103].

5.4 Writing the Brain: An Interdisciplinary Collaboration Between Neuro-Engineering and Writing

As a collaboration between the creative writing workshop led by Cristina Rivera Garza in the department of Hispanic Studies and the department of Electrical and computer Engineering, at the University of Houston, we organized a neuroscience-integrated creative writing workshop that addresses the topics of writing as a community practice, writing through our bodies' experiences, and unconstrained in terms of creative production. Through this transdisciplinary collaboration, we have a window into human creative expression in the field of creative writing as it occurs naturally and without behavioral or movement constraints. At the same time, students were able to see and experiment with neurophysiological activity as they engaged in their writing exercises; a window into the inner workings of their bodies from neural data.

Two creative writing workshops in Spanish, talleres de escrituras [98], were conducted with mobile EEG technology. The first workshop intended to explore differences in EEG brain activity patterns between preparation and production stages of the creative writing process. The students wore 4-channel dry, wireless, EEG headsets as they a) walked through spaces in the city based on writing prompts and b) when they were creating the writing drafts. The second workshop was aimed at understanding effect of the workshop intervention (readings, lectures, visiting specific locations, during text workshopping –tallereando- [98] their texts) on brain activity patterns, and tracking this brain activity at the workshop sessions where students commented and conversed about their peers' texts. In this second workshop, there were four EEG recording sessions, all inside the classroom: at the start of the semester (before the workshop) with writing prompts, two times during text workshop sessions, and at the end of the semester (after the workshop) based on writing prompts—physical locations in the Houston Second Ward.

We aim to develop a predictive model of brain dynamics associated to the process of creative writing composition though mobile brain-body imaging. This model could have transformative impact on promoting and assessing creative skill development, personalized education and innovation.

5.5 Experiment Design

Readings and prompts asked students to acknowledge the physicality of the writing process and to relate it to the materiality of language. Prompts issued in this upper-division undergraduate workshops asked students to develop and record a series of specific movements (walking, running, climbing) as they completed the required assignments.

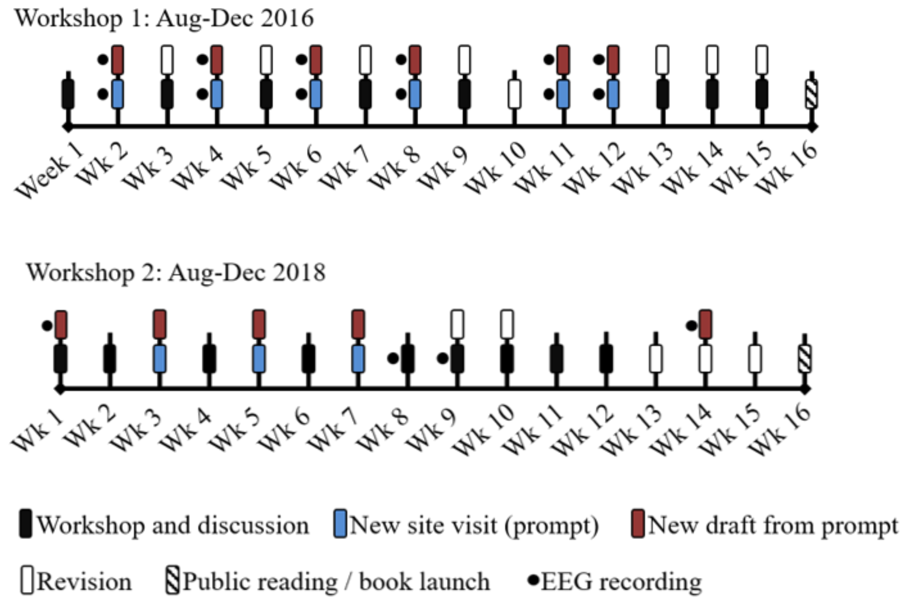

Figure 5.1: Timeline for workshops: talleres de escrituras. The site visits in Workshop 1 were optionally individual visits, while for Workshop 2, these were group visits.

Workshop 1: Mobile EEG While Walking Spaces in the City (Preparation) and Drafting Texts (Generation) Stages

Seven Spanish and English-language bilingual students collected dry mobile EEG data in the creative writing workshop. The students were trained on how to operate the mobile EEG headsets, check for good channel contact and data quality, record their own data. They kept a journal of their wanderings, including recording time and location.

Mobile EEG (Interaxon, Muse) data was recorded during the five data walking sessions (preparation stage) and during their writing (production) of first draft of texts for each prompt. EEG data was collected at 250 Hz, head acceleration at 50 Hz, and connection quality (electrode contact) at 10 Hz.

The data quality was a challenge as the dry EEG electrodes often lost contact with the scalp (there were no aids used to hold them in place other than the headset design itself), and data was lost due to improper saving procedure or battery drainage. Data from seven subjects, over 18 recording sessions was deemed of good quality to continue to work with.

5.5.1 Workshop 2: EEG Recording Before and After Workshop Intervention

Eight bilingual students participated in a creative writing workshop over the course of a semester. EEG data was collected in two sessions of creative writing and two sessions of discussion of their creative texts during the workshop. This experiment analyzes the effect of an intervention on training individuals and concomitant neural changes on improvisational creative writing performance.

Brain activity was collected with 32 gel-based active-electrode EEG sampled at 1000 Hz. The electrodes were placed in accordance with the 10–20 international system using FCz as reference and AFz as ground. A synchronized video camera was used to record the experiment.

The students wrote creative texts while wearing the EEG equipment in two time-constrained creative writing sessions: one before the workshop, in week 1; and one after the workshop, in week 16.

During the time-constrained improvisational creative writing sessions, the students were given three writing prompts (2min each), preceded with periods of baseline with eyes open (1min), baseline eyes closed (1min), and a control condition where they transcribed a text (2min).

5.6 Discussion: On the Question of Authenticity

We built a neuroscience-integrated creative writing workshop in an effort to provide robust and insightful empirical knowledge in a truly transdisciplinarity experiment.

In the first workshop, we envisioned an experimental protocol that would allow creative production and evaluation in a real-world setting, without movement constraints, in which participants could feel free to move, interact, and respond to environmental queues. Portable, mobile EEG headbands were given to the students to use on their walking prompts and while writing their creative drafts. Although dry, mobile EEG technology is available, its use in walking real-world settings proved to be difficult for the students. Only seven students finished the pilot study wearing the EEG headbands; as they decided to reduce distractions and reduce set-up time for their creative activities. This pilot study provided clear empirical results from which to base a following hypothesis based on the potential for PDC between left-frontal and right-parietal scalp areas as a characterizing feature in creative writing.

In the second workshop, based on the experience from the first one, we decided to track the development of the students' neural features through four data collection sessions: 1) before the workshop, 2) after the workshop, and 3-4) two sessions during the workshop in which students would discuss and comment the texts from their peers[2]. Here, gel-based 32-channel EEG recording devices were used in a laboratory-setting: students were sitting as they worked through the experimental tasks. This setup allowed us to test for PDC and other neural features candidate for characteristic of creative writing.

[2]The workshop sessions where students discussed their texts were not analyzed as part of this dissertation.

These two experiments in the context of talleres de escrituras are the first neuroscience study in the context of real-world creative writing. These studies track the brain-activity underlying the creative writing process in its stages, from skill development to the embodiment of the process (visiting the locations), to making drafts, discussing them, and editing a published book as a final product (Fig. 5.1).

5.7 Acknowledgements

This research was funded in part by NSF award #BCS1533691, NSF IUCRC BRAIN Award CNS1650536, a Seed Grant from the Cullen College of Engineering at the University of Houston, and the SeFAC grant from the Center for Advanced Computing and Data Science (CACDS) at the University of Houston.

5.8 Author Contributions Statement

JGCG wrote the first draft of the manuscript. JGCG and CRG planned the experiments and data collection mechanisms. JLCV and CRG conceived the research and edited the manuscript. All authors reviewed the manuscript.

Chapter 6

Characterization of the human creative process in the visual arts: The Exquisite Corpse

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6.1 Abstract

Progress in in the neuroscience of the human creative process has seen increasingly creative methods researchers are relying on to study its origin and dynamics; beyond simple paper-and-pencil tasks or cognitive tests. Here, we propose a protocol to study the human creative process in the visual arts where three artists at a time collaborate in an improvisational composition based on the Exquisite Corpse, a game created by the Surrealists in the 1920s with elements of drawing, collage, surprise,

[1]To be submitted as a journal article in 2019-2020. The chapter organization is based on the template from the journal Scientific Reports.

organic collaboration, and improvisation. We use mobile Electroencephalography and Inertial Measurement Units to analyze the artists' creative actions and augment current models of creative cognition with Mobile-Brain Body Imaging technology in natural, contextual settings.

Six artists' creative actions were segmented into 9 classes pertaining to two rest conditions (eyes closed and eyes open), planning, creative execution with elements of drawing and collage, writing, and correction. The most relevant motion features for the artists' creative actions were the log magnitude ratio between the jerk of right and left hands, the angular velocity in the y-axis of the right hand (parallel to the drawing plane), and the sum of the acceleration magnitude from both hands. EEG data was analyzed through classical machine learning and automatic feature extraction algorithms with convolutional neural networks. For EEG classification, the segmented classes were reduced to: Baseline Eyes Open, Baseline Eyes Closed, Planning, Mark Making, and Writing. The successful classification (53.5% accuracy) based solely from mobile EEG features in temporally isolated data samples across artists indicates that neural dynamics pertaining to contextually-meaningful creative actions share common information between them: even when the artists produce different compositions between each other or across time. The EEG features driving classification performance were an even combination of band-power and pair-wise information transfer features between right parietal, central, and lateral frontal regions of the scalp. These results characterize the human creative process in the visual arts, in action and in context, by revealing a network of right-parietal, and left-frontal brain regions activating in the Mark Making and Writing creative actions, with predictive power across different artists.

6.2 Introduction

Research on the human creative process today acknowledges that creativity research is a transdisciplinary endeavour enhanced by input from experts in their creative field meeting researchers in their measuring capabilities to study an aspect of the creative process [1]. Progress in in the field has seen increasingly creative methods researchers are relying on to study its origin by going beyond simple psychometric tests, evaluation tasks, or a relationship between and instead focusing on more context-relevant settings [104]. For example, studies on creative performance have been conducted in dance through MoBI technology [19]; while functional magnetic resonance imaging (fMRI) has been deployed to investigate creative writing in poetry composition and revision [60], action planning while imitating chord progressions comparing classical and jazz-trained pianists [61], musical improvisation using pitch sets or cue words in pianists [62, 105], or semi-professional visual artists sketching drawing ideas for a book cover based on sets of descriptions [63].

These experiments provided valuable data into some of the major gaps in creativity research[106]: spontaneous creativity [61, 63, 60, 21], and motorically complex forms of creative production[19, 1, 21] and perception [20]. This report focuses on the visual arts, using Mobile Brain-Body Imaging (MoBI) with mobile Electroencephalography (EEG), inertial measurement units (IMUs), and behavioral annotation through video recordings of three artists working together in an improvisational creative composition.

In a discussion [1] about the significance of transdiscilinarity in experiment design to ensure valuable hypothesis generation and authenticity in the creative experience for participants in creativity experiments, we proposed the an experimental protocol in which artists follow the spirit of the Exquisite Corpse for creative improvisation and collaboration.

The protocol is defined in the spirit of the Exquisite Corpse, a game invented by the Surrealists in the 1920s that consists of building a three-part improvisational piece from the contributions of different players [74]. By adapting the Exquisite Corpse, which incorporates improvisation, collaboration, and organic problem solving as experiment design, we can merge the long tradition of the arts exploring the inner workings of the mind, and the growing field of neuroaesthetics into a MoBI protocol in a collaborative setting between professional artists (or non-artists: see [1]), without movement constraints.

The Exquisite Corpse was originally conceived as a word-based parlor game relying on collaboration, chance, and unexpected juxtaposition. The game involved three to four players that wrote a phrase on a piece of paper, then they folded and passed the sheet to the next player to continue writing. In the visual imagery version, the players would aim to create a "body" consisting of head, torso and legs or tail. Players are allowed to see the edge of the previous composition to begin their own. Other art forms such as dance, music, and poetry have also adapted the game for their respective genres [1].

As human creativity is likely to emerge from the interaction of multiple affective, cognitive and movement processes, the study of the human creative process benefits from creative tasks that enable the participants to experience a range of creative decisions, and move away from experiments that focus on a simple measure or task. The consistent findings in creativity studies have provided evidence for the involvement of the prefrontal cortex in creative ideation, and in the case of EEG, an increase in alpha (8-12 Hz) band-power as a function of creative tasks or creativity level [14]. These findings, together with those found in poetry composition experiments in fMRI, have been summarized in [60] to propose a model for creative production and revision. The model proposes that there is inhibition of the dorsolateral prefrontal cortex (DLPFC) in the production of the creative product, increased cooperation between the DLPFC and ventromedial prefrontal cortex (VMPFC) during revision and evaluation of the work, and increased coupling between these two regions during the planning component of the activity. Research suggests fundamental cognitive functions (integrating highly processed information, abstract thinking, cognitive flexibility, etc.) of the prefrontal cortex[64] as central in forming the foundation for original thoughts from which creative cognition can emerge.

Studies have also implicated the parietal lobe as heavily connected to creative activity—both spatially and emotionally. Overall, parietal regions have been recognized as significant for body-environment interactions (specifically for visual exploration, motor use of the hands, and tool use). Recent research also supports the importance of the parietal region in higher-order processes such as multisensory and sensorimotor assimilation, spatial orientation, motivation and intention, and the representation of the external environment's relationship to the body [70]. Research has also found the contributions of the parietal lobe as extending to cognitive functions such as episodic memory retrieval: consciously accessible memory for specific events that allow humans to retrieve past experiences and employ them for future goals. A literature survey performed by Wagner et al. [72] revealed that fMRI as well as EEG studies on episodic retrieval have highlighted significant activity in the temporal and lateral posterior parietal cortex. These tools, including visual exploration, motor capabilities, tool use, spatial orientation, motivation, and memory retrieval, amongst others, are central to the creative process of generating art.

6.2.1 Hypothesis

We aim to expand on the proposed models by including information from mobile EEG features associated to creative cognition in real-world settings, where participants are free to compose their work as an improvisational piece. Frontal, Parietal, and motor areas of the brain were expected to be modulated with creative actions performed by the artists, and we expected information transfer dynamics to be most evident during creative production.

We also expected that such brain patterns tagged to creative output may show neural individuality and variance across participants, modulated by situational context, demographics, and other factors yet unknown.

6.3 Results

6.3.1 Creative Actions and Class Labels

In the Exquisite Corpse experiments, we annotated the data by having human annotators watch the video recording of the artists as they worked on their artwork. The classes were selecting according to the stages of the human creative processed proposed in previous literature: baseline conditions, planning, execution, revision (see Supplementary Materials Table 10.1). Valuable and reliable labels were discussed and analyzed with the professional artists [1] that participated as subjects in our study through interviews, relation to art theory, and formal discussions between the fields in scientific conferences [35, 104] and in discussion meetings. The Exquisite Corpse in the visual arts involves elements of collage [107] and drawing [108], captured broadly by the following stages of the creative process and execution tasks: Baseline Eyes Open, Baseline Eyes Closed, Plan, Drawing or Tracing, Coloring or

Shading, Cut, Paste, Writing, Revision.

The sections of the experiment for each of the two Exquisite Corpse renditions are described schematically in Fig. 6.1A. For each artwork, each artist completed one third of the figure, Section 1 to 3. The experiment was preceded by a 1min Baseline with Eyes Open (rest) looking at the blank triboard, and a 1min Baseline with Eyes Closed. The generated artworks from the experiment are shown in Fig. 6.1B. The artists that generated each piece are identified from 1-6 as A1-A6, respectively. Each artist was able to see 1-3 cm of the previous artist's contribution to continue the collaborative artwork.

The class vectors for each of the six artist, A1-A6, are shown in Fig. 6.2. Fig. 6.2A shows the class vectors for the first rendition of the experiment with three artists, and Fig. 6.2C shows the corresponding class vector for the second rendition of the experiment. The solid black lines indicate that a new Section started, and the dotted lines indicate that the corresponding Section ended. Fig. 6.2B and Fig. 6.2D display the proportion of time-samples between the annotated classes. Fig. 6.2E contains the class label key; and Fig. 6.2F displays the total number of samples per class among all artists. From the initial nine classes, the class Cut was removed from analysis to leave only those associated with creative production and rest, and the class Correction was removed because of its low number of samples; leaving seven classes to analyze.

From this initial segmentation of the data, we selected five major classes to analyze[2]: Baseline Eyes Open, Baseline Eyes Closed, Plan, Mark Making: Execution-related classes (Drawing or Tracing, Coloring or Shading, and Place), and Writing. The Writing class was separated from the other Execution-related classes.

[2]Classes for EEG data analysis: Baseline Eyes Open (BO), Baseline Eyes Closed (BC), Planning (Plan), Mark Making (MM), Writing (Wr). The class Mark Making contains what was originally segmented as: Drawing or Tracing, Coloring or Shading, Paste. See Supplementary Materials Table 10.1. The class 'Correction' was removed due to low number of samples per participant.

Figure 6.1: Schematic diagram of the Exquisite Corpse protocol for the visual arts and three creative outputs from the experiment. A) Schematic diagram. B) Experimental task artwork production from one group of three artists.

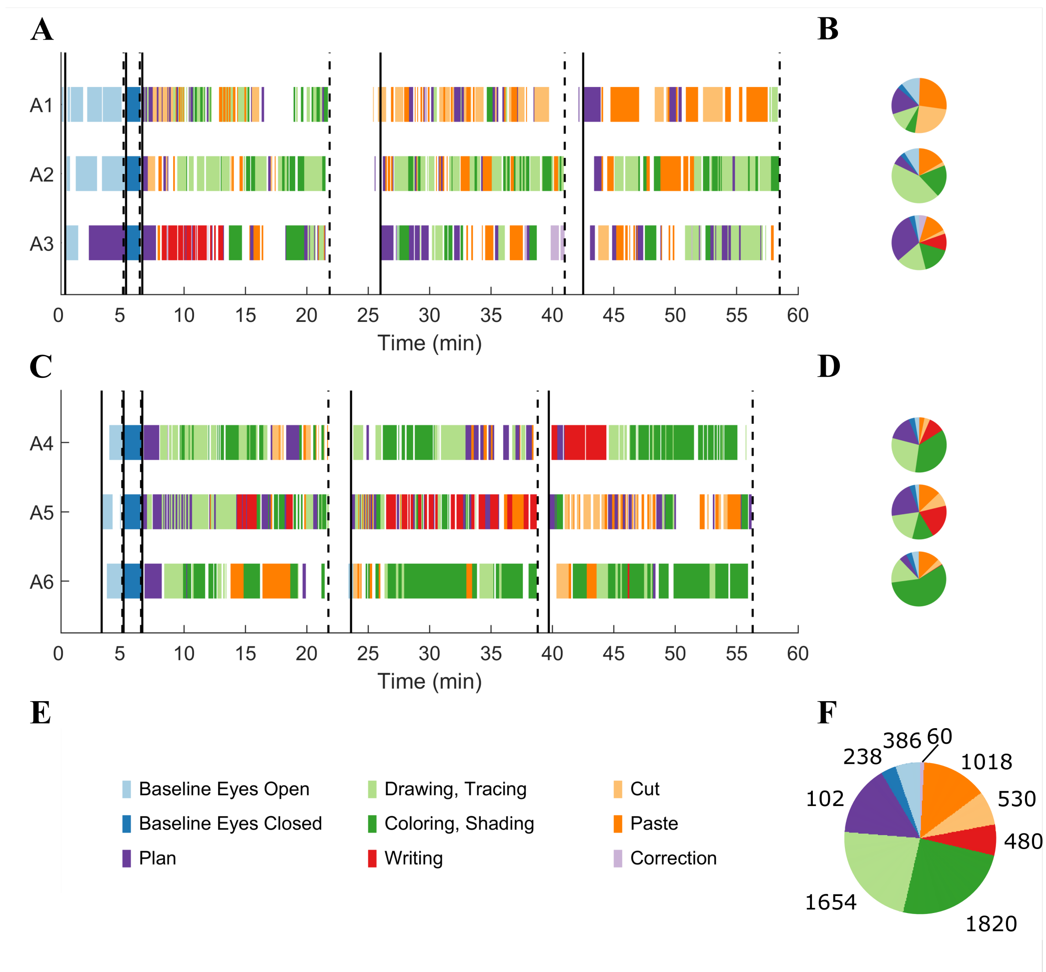

Figure 6.2: Examples of the class vector for six artists that participated in the Exquisite Corpse for the visual arts. Black lines indicate the start of a new section; dotted black lines indicate the end of a section.

6.3.2 Kinematics

The mutual information based feature selection algorithm, maximum relevance - minimum redundancy (mRMR) [42], suggested that the log magnitude ratio of the motion jerk, the bilateral magnitude of the acceleration, and the angular velocity in the y-axis left-to-right movement parallel to the plane of the artwork were the most informative features related for the nine creative actions visually segmented from the video recordings described in Fig. 6.1 and Fig. 6.2.

Fig. 6.3 panels C and D provide a visualization for the kinetic components of the creative behavior observed and annotated; along the three most relevant features: The angular velocity in the y-axis is shown in the vertical axis, the log magnitude ratio of the jerk is shown in the horizontal axis, and the bilateral magnitude is displayed in the z-axis. The visualization in feature space provides a glimpse into the overlap of the classes in motion space. In Fig. 6.3C, the classes Plan, Paste, Drawing, and Writing overlap, while Coloring appears to be more separated in the jerk log magnitude ratio. The baseline classes overlap with each other in motion space. Fig. 6.3D combines the Mark Making classes together, placing them in between the Writing and Plan classes in kinematic feature space. The baseline conditions contain small movement amplitudes in any of these features, while the Planning and Cut classes occupy a mid-range section of the feature space. Finally, the Mark-Making classes are found on the larger ends of the feature space.

6.3.3 EEG

The EEG feature space representation for all classes analyzed is shown in Fig. 6.3 panels A and B, for seven and five classes, respectively. The class for Baseline Eyes Closed is the most separated from the other class, particularly in Parietal Gamma

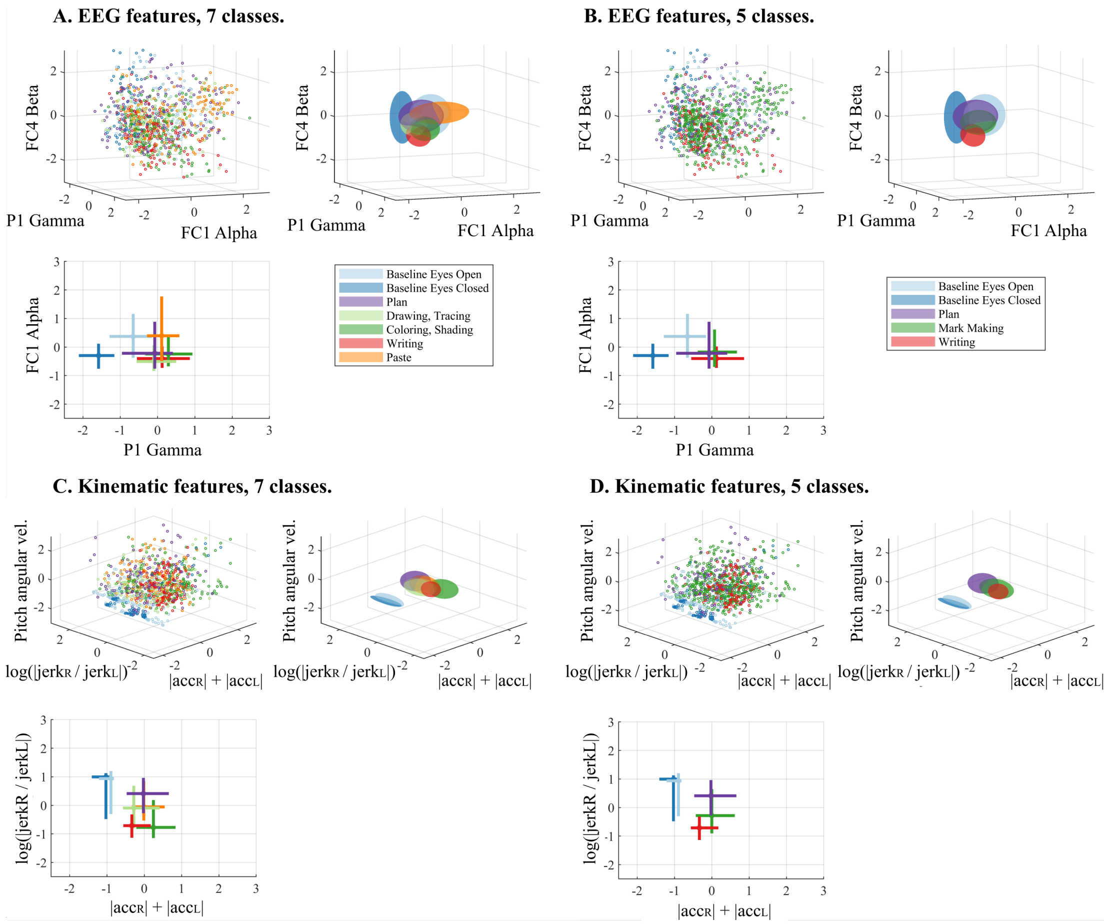

Figure 6.3: Feature space characterization of the seven creative classes selected for analysis. The classes Paste, Drawing or Tracing, and Coloring or Shading. in A and B were collapsed to Mark Making in B and D.

power content. The creative classes overlap in the center, but with differences between them. The Writing class is the most separated class in Fig. 6.3A and B, while Plan, Paste, Drawing, and Coloring cluster together in the middle. In 6.3B, with the Mark Making classes together, these classes appear to occupy a feature space between Writing and Plan in the features FC4 Beta power, and FC1 Alpha power.

A spatial representation of the most discriminant EEG features per class is shown in Fig. 6.4 for band power analysis and Fig. 6.5 for PDC analysis. The features are plotted on scalp maps. The features plotted are those which showed significant statistical differences from Baseline Eyes Open, at a Bonferroni-corrected significance level of 5% for the band power[3], and at 0.1% for the PDC features[4].

Band Power Analysis in EEG Features

The band power features shown in Fig. 6.4 provide a visualization into the activation of brain areas involved in the human creative process.

First, Baseline Eyes Closed (BC) was used as a control condition to find common neural patterns known to be found when humans close our eyes; in particular, there is high alpha synchronization (more power) in occipital areas. An overall increase in alpha power throughout the brain was consistently found among the artists.

In the Plan condition, there is a clear desynchronization (less power) in central locations in the beta band, and stronger in right locations. These areas are involved in movement coordination. There is synchronization is parietal and occipital and parietal regions in the gamma band, accompanied by desynchronization in the delta and theta bands. Modulation in parietal regions is associated with spatial planning

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[4] Bonferroni correction for 5% significance level: $p < 0.05/(5 \text{ frequency bands} \times 60 \text{ channels}) = 1.67 \times 10^{-4}$.

[4] Bonferroni correction for 1% significance level: $p < 0.01/(5 \text{ frequency bands} \times 28^2 \text{ connections analyzed}) = 2.55 \times 10^{-6}$.

in creative work [60].

In the Mark Making condition, there is a large desynchronization in the delta and theta bands in occipital regions. In the delta band, the there is a strong desynchronization is in pre-frontal and right temporal locations. The pre-frontal cortex is associated with executive function and is the most consistent finding as a modulating feature (activations and deactivations) in the human creative process [14, 10]. The theta band shows synchronization in central and mid-frontal locations.

The Writing condition follows similar patterns than the Mark-Making condition, with overall larger amplitude change than in Mark-Making.

All creative classes show a dominant increase in alpha power in frontal and pre-frontal locations, while Baseline Eyes Closed includes an increase in alpha power in occipital areas.

PDC Analysis in EEG Features

The PDC features shown in Fig. 6.5 provide deeper insights into the flow of information between electrode locations over the scalp. The most salient features come from the Mark Making and Writing conditions, the the top 1% change, compared to Baseline Eyes Open, in positive and negative occurred. There is a decrease in PDC from left frontal to parietal and occipital locations, more pronounced in the theta, beta, and gamma bands.

In the Mark Making condition, there is an increase in PDC from occipital and parietal regions to mid-frontal locations in the delta and gamma bands, with reaching pre-frontal locations in the alpha, beta, and gamma bands.

A similar pattern occurs in the Writing condition, with the major difference being the reduction of occipital to frontal connections in the beta and gamma bands.

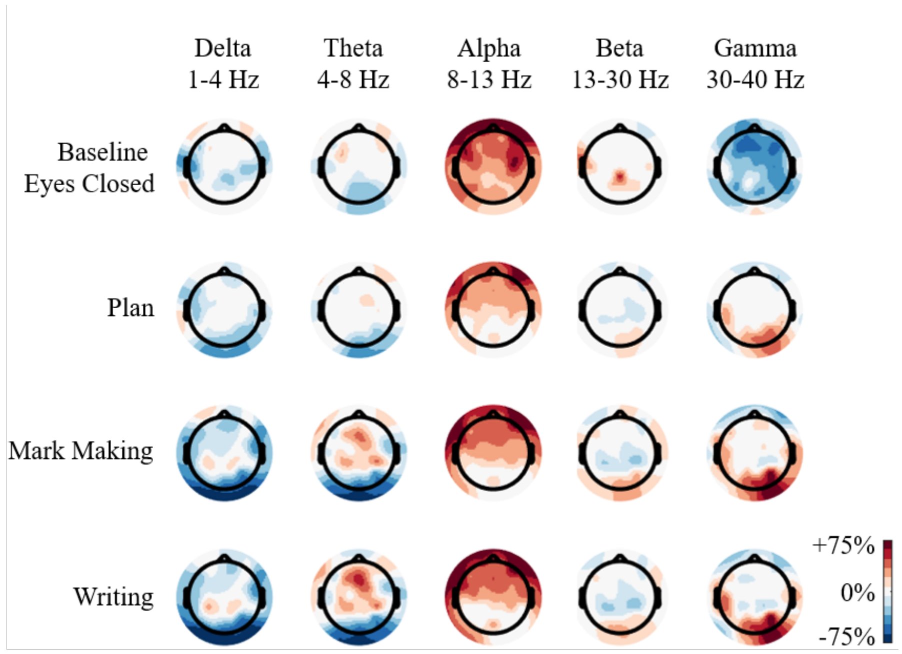

Figure 6.4: Characterization EEG features for classes compared to Baseline Eyes Open. Percentage of power change per frequency band analyzed.

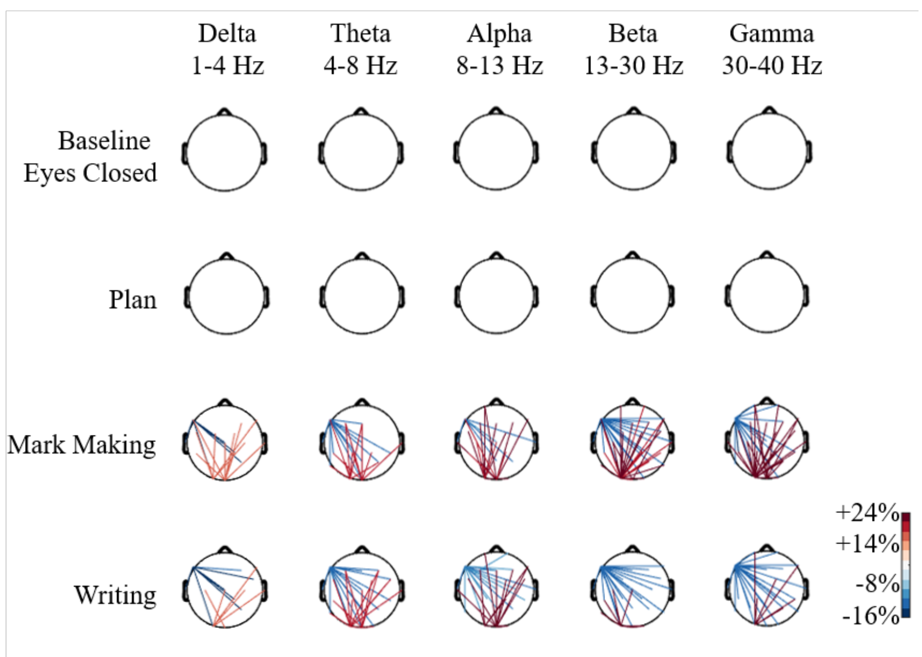

Figure 6.5: Characterization EEG features for classes compared to Baseline Eyes Open. Percentage of PDC change per frequency band analyzed. The top and bottom 1% change across classes is displayed.

kSVM Classification Results

The selected classes were classified using kSVM of polynomial degree 3, after selecting the 50 most relevant features in the EEG data, and the 8 most relevant features in the Kinematics data. These features were selected using the mRMR algorithm, which selects the most relevant feature based on the mutual information shared between the features and the class vector, and subtracts the average mutual information shared between the selected feature and the previously selected features.

The classification was performed for the seven (Fig. 6.6A-C) and five (Fig. 6.6D-F) class schemes; for EEG features alone, for Kinematic features, and for a combination of EEG and Kinematic features.

The most relevant EEG features for classification among the seven classes, in order of relevance and minimal redundancy from mRMR were: Alpha power in F4, PDC from FC5 to P8 in the Beta band, Gamma power in FC4, Delta power in Oz, PDC from O2 to CP1 in the Beta band, and Theta power in TP8. A full list of the 50 features is shown in Supplementary Materials Table 10.2. In the most relevant, and minimally redundant, 50 features, 19 of them were PDC features. This feature ranking list suggests that PDC and band-power features contain complementary information for classification of creative actions.

The classification accuracy with EEG features for five classes achieved a mean of 53.5% (20% chance level); and 35.9% for seven classes (14% chance level). These results provide the first evidence that it is possible to classify tasks related to creative production in the visual arts through neural features alone: in unseen data taken from temporally different task incidences. Mark Making is confused primarily with Planning and Writing. In the Kinematic domain, the Writing class is well classified, which indicates that this class is different in motion space than the rest. Its higher confusion rate in the EEG domain suggests that there are more similarities in neural

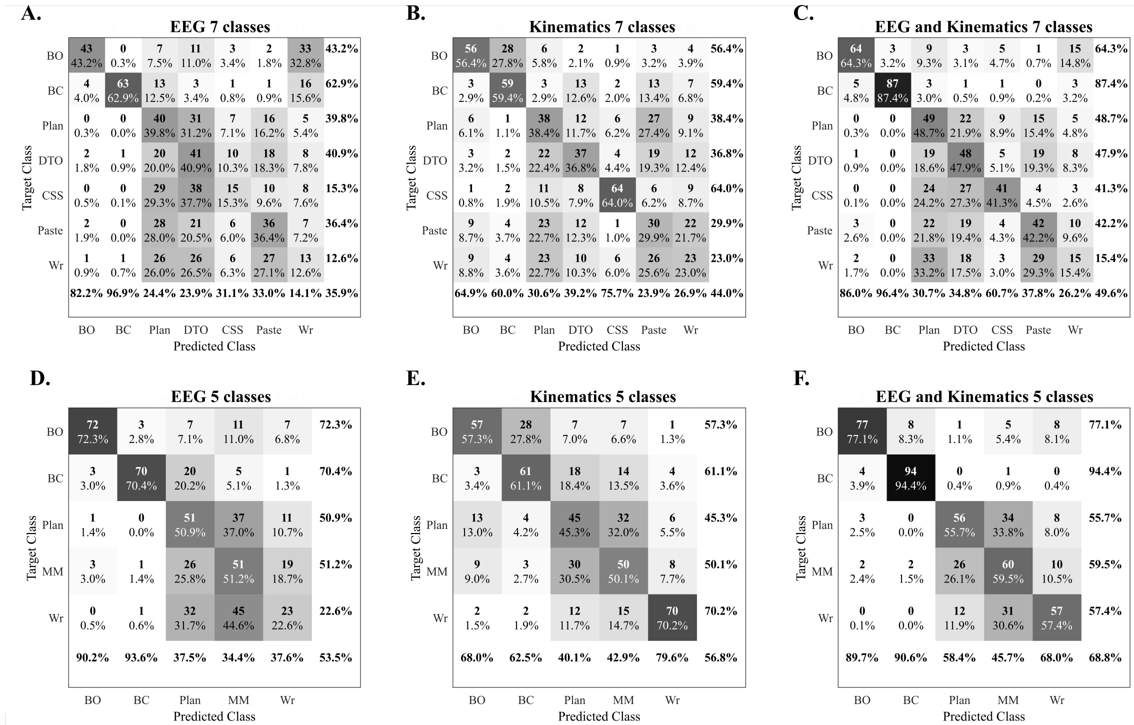

Figure 6.6: Confusion matrices for the mRMR-kSVM classification results. A) Random subsampling in the test set. B) Temporal subsampling in the test set.

features involved in these two creative execution tasks.

The classification accuracies improve with EEG and Kinematic features together. This machine learning scheme achieves 49.6% for seven classes, and 68.8% for five classes. The classification results improved with a combination of EEG and Kinematics features, showing that they provide complimentary information about the creative classes analyzed.

EEG CNN Feature Visualization

In neuroscience, we are interested in understanding the neural features that contribute to the classification of tasks. In this unconstrained experimental setting with multiple and varied actions performed by the artists, these features may be a combination of several different cognitive processes acting together. Therefore, visualizing the features learned automatically is critical to understand the performance of the classifier [109, 110], and verify that the results are in fact driven by neural information.

We performed two methods for important feature visualization: 1) Causal effects of the feature values on the outputs (input perturbation-output correlation): how much does the output change if we perturb the input? 2) Find the best examples (highest activation in the last layer before Softmax) for each class and compare the spectral differences between them.

The input perturbation consisted of transforming an EEG channel into the frequency domain, adding noise (0-5% of the total power) to a frequency band of interest (i.e. delta, theta, alpha, beta, gamma), and transforming back to the time domain. The output, before the Softmax layer, was saved for each perturbed data sample, for each channel and frequency perturbation. 300 data samples per class were randomly selected for analysis. The known input perturbation was correlated with the output before the Softmax layer across 300 samples per class. 97% of the samples were classified the same way before and after the perturbation, validating that the noise added disturbed the EEG in a plausible way (not too much to make it unrecognizable). The results of such analysis are shown in Fig. 6.7.

The most salient correlations, Fig. 6.7B, occur in the gamma band for all classes. The gamma band feature perturbation, with up to 3 times the standard deviation of the frequency band power per channel is most susceptible to cause changes in the nodes before the SoftMax layer in the gamma band. The gamma band is a frequency band of interest for the CNN.

Other patterns are also evident from Fig. 6.7B. There is a negative correlation

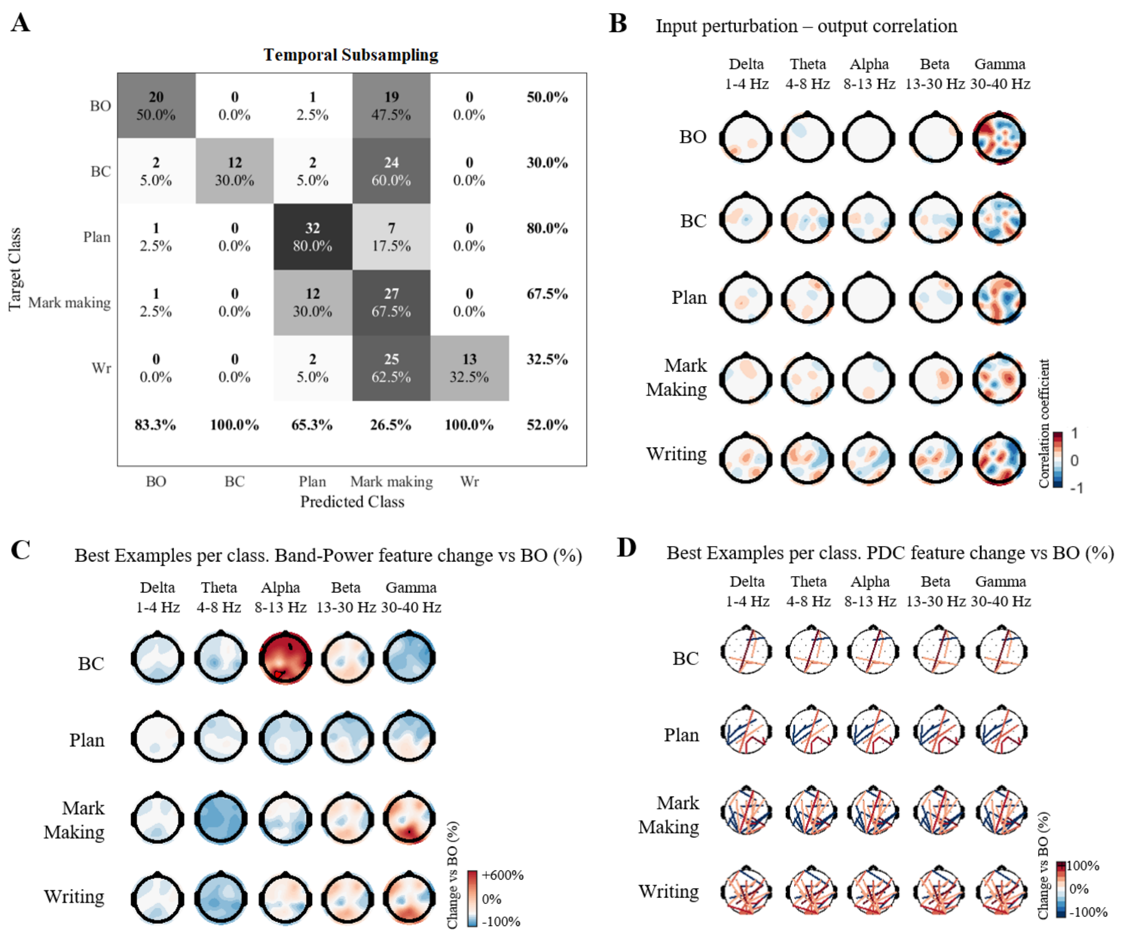

Figure 6.7: CNN classification results and feature visualization. A) Confusion matrix in the test set. B) Input perturbation - output correlation. Best examples per class vs BO: C) Band-power change. D) PDC change.

with increase of band power in central channels in the alpha band for the Planning class, which is consistent with the relevant feature findings in Fig. 6.4.

The Writing condition is the most susceptible to changes based on input perturbation, especially in central-frontal and parietal electrodes.

We would expect high activation in the occipital electrodes for the "Baseline Eyes Closed" class, as the visual cortex is known to undergo alpha-synchronization when a person closes their eyes. The correlation is not evident here because the perturbation is too small.

Fig. 6.7C displays the results of the spectral power in the 100 best examples from each class, taken from the whole training set (not only 300 samples per class): those which yielded the highest activation in the last layer before the Softmax for each class and therefore those which the network found to be most representative of each class. The spectral power in each class was compared to Baseline Eyes Open.

Here, we see similar patterns as in Fig. 6.4, validating that the network effectively considers those features (frequency band and channel location) important for classification. In this visualization method, we observe an increase in power in the occipital area expected for Baseline Eyes closed: the increase in power is in the order of 500%, not captured by the 0-10% added noise in the correlation analysis. In this visualization of the best examples per class, we see deactivation across frequency bands for the frontal and pre-fronal locations in the Planning condition. There is strong deactivation of the theta band across the scalp, coupled with increased gamma power for the Mark Making class; as well as alpha deactivation exclusively in central regions: consistent with alpha deactivation in motor tasks.

The best examples of data windows for each class were analyzed in terms of their PDC activations as well, in Fig. 6.7D. The top 1 percentile and the bottom 1 percentile of the connection strength distribution is plotted. There are connectivity patterns across all classes, suggesting that this was not the only discriminant feature found by the CNN. However, the Mark Making and Writing classes contain the most connection differences between the parietal and central-frontal electrodes, making a clear connection with the classical feature extraction techniques used in Fig. 6.5.

6.4 Discussion

6.4.1 Motion analysis in the visual arts

The most relevant motion features, those which shared the most mutual information with the class vector and least redundancy with previously-selected features, were the jerk log magnitude ratio between the right and left hands, and the angular velocity in the y-axis of the right hand. The bilateral acceleration of the right and left hands was also a feature that contained relevant separable information between the classes analyzed.

The feature maps in Fig. 6.3C-D provide a motion feature space representation of the creative work from each artist. The artists' work was displayed quantitatively, with distribution of the artists' movements and the overlap between the different actions that form the artists' creative process. This representation of the human creative process augments the information obtained not only about the artwork, but about the process itself, which was previously only glimpsed at by observation of the final product itself or, occasionally, by filming the artist at work. We propose the representation of the artists' work in motion feature space as a quantifiable blueprint of the artists' process.

The distribution of the tasks analyzed in this feature space varied by artist (see Supplementary Materials 10.1, 10.2, 10.3), which enables the characterization of the creative tasks and the artists' individuality in their creative process. The feature maps also show a degree of consistency among the artists: the baseline tasks show little movement, shown in the lower left corner; while the planning, collage-related actions (cut, paste) appeared in the mid-level of motion; and drawing or writing tasks show the largest amount of motion, and distribution spread.

6.4.2 Classical Machine Learning vs Deep Learning for EEG

The vast literature in EEG and in motor and cognitive tasks has focused in analyzing primarily three types of features from the data: power spectrum-related features, time-domain features, and connectivity or information shared between electrodes. In typical EEG experiments, the subjects' task is constrained within a laboratory setting, or in a particular motor or cognitive tasks, repeated a number of times to obtain Event Related Potentials after averaging multiple windows of data. These experiments have proved useful in identifying relevant EEG features for cognitive and motor task decoding. We used some of the most widely used features, in the connectivity and frequency-domain, to guide the classical machine learning analysis. This approach proved successful in the classification of the behavioral tasks undergone by the artists to produce the artistic output, yielding 53.6% accuracy for five classes using only EEG features, and 68.9% accuracy using EEG and Kinematic features.

A data-driven approach to obtain the relevant information directly from the data, without hand-crafting the data features, shows promise to uncover neural patterns that may be relevant to the specific task at hand.

In our analysis, the accuracies obtained by the CNN approach did not improve on the accuracies obtained in the mRMR with kSVM paradigm. However, it does demonstrate the potential of the technique to find relevant classification features directly from the data, with pre-processing that can be performed online. A limitation of the CNN approach is that the optimal architecture may require a iterating through different models and parameters. Further, as we move towards big-data in neuroscience, with researchers procuring the data collection, storage, and systematic dataset collection [111, 22, 112, 113, 54, 21], the possibility for large scale, high quality, and labeled EEG data in a variety of tasks makes the deep learning approach appealing for automatic feature identification and classification.

6.4.3 EEG Automatic Feature Extraction and Visualization

The proposed learned feature visualization techniques for the CNN framework provides a way to identify the features that the CNN is learning from the data. The increase in alpha power in the occipital areas when a subject closes their eyes was clearly identified by the network as the most distinct feature between baseline eyes closed vs baseline eyes open (Fig. 6.7C).

The integration of information from the input-perturbation output-correlation, and the best examples by class activation score visualizations, along with the researcher's interpretation of the results is necessary to understand the features that the network finds relevant for EEG data classification. Frontal and parietal areas are consistently shown as the most different in terms of band-power Fig. 6.4, and Fig. 6.7C between baseline eyes open and Mark Making (more frontal dependency), and planning.

6.4.4 EEG Feature Relevance and Interpretation

The EEG features selected for classification through classical machine learning produced 53.6% classification accuracy for a five class problem (chance level: 20%), using temporally isolated samples from all six artists. Even when the artists were producing different compositions between each other, and in time, the EEG features associated with their creative process had the discriminative power to predict what the artist was engaged in, based only on a data sample (4s, 60-channel) of EEG data.

The features driving classification were obtained both through classical feature engineering methods with frequency band-power and PDC features, and through a CNN-based automatic feature extraction algorithm. Through feature visualization, we found a significant overlap between the neuroscience-engineered features, and the automatically extracted features.

The most relevant features for classification among the five classes spanned the frequency bands evenly, and a Band-Power and PDC features were similarly relevant with 31 and 19 features selected respectively. The most relevant feature was alpha band-power in F4, a right-frontal electrode. This feature is clearly a discriminant between the baseline eyes closed and the rest of the classes, but it is also around the electrodes where relevant PDC connections start or end. The second most relevant (and non-redundant) feature is PDC from the left-motor regions (FC5) to right-parietal areas (P8), which were shown as the most discriminant features from the feature visualization techniques: There is an increase in connectivity magnitude associated to the human creative process from motor and somatosensory areas towards parietal and occipital areas of the brain; across frequency bands 6.5. Gamma power in left and right frontal regions follow as the most relevant features, indicating again the relevance of the frontal cortex in the human creative process.

The feature visualization methods provide information on what features drive classification performance. The creative writing tasks were found to have the highest PDC changes compared to baseline among all the classes analyzed, suggesting that semantic processing activates functional connectivity patterns to a higher degree than planning or other physical mark-making actions.

6.4.5 Extensions for Analyzing the Creative Process in the Visual Arts in Real-World Settings

The analysis of the deep learning framework of EEG data is limited by the amount of data available per subject. A common protocol across with freedom of movement and creative possibilities has the potential to uncover common and unique neural patterns associated to the human creative process. In a larger population of artists and not-professionally trained artists, the neural patterns associated to creative improvisation in the visual arts can be compared at population-level. For such analysis, leveraging machine vision behavioral segmentation techniques would be useful for the automatic classification of creative actions from the artists. Future iterations of real-world neuroscience experiments on the visual arts can benefit from advances in the field of machine vision, but they need to provide accessible video feed for those algorithms to perform appropriately.

The limitation of the need for labeled data, and the scarcity of data in a specific protocol remain the largest limitations. Classical machine learning techniques have shown to perform as successfully than the proposed deep learning approach. Abundance of data has propelled automatic feature extraction techniques to better performance in other fields, so we expect that as real-world neuroimaging technology becomes available [21], the wealth of data will increase together with it and provide automatic feature extraction algorithms the data they need to perform to their optimum level.

6.5 Methods

Brain activity was collected with 64 active-electrode wireless EEG. Four electrodes were used for EOG recordings. IMUs were used to track head and body motion data from the artists that capture the creative gestures of the performers, while providing useful information for identifying potential motion artifacts. IMU data were collected from the head and forearms. Video cameras placed directly above each artist and artwork captured the development of each work of art. An example of the experimental setup with sample EEG, acceleration, and video data is shown in Fig. 6.8.

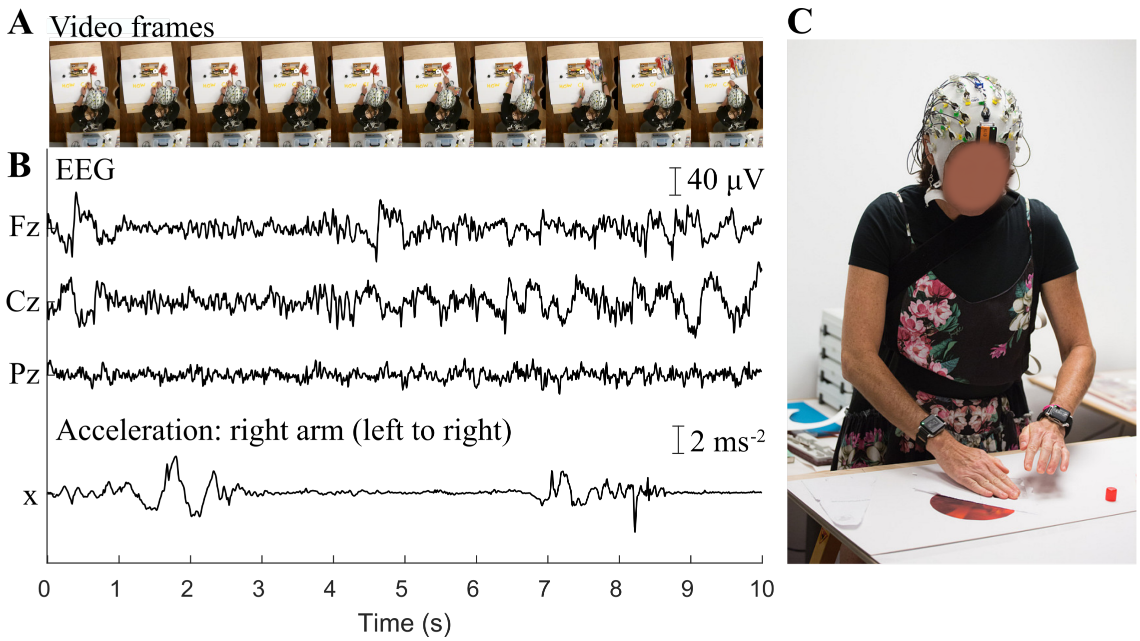

Figure 6.8: Experimental setup for the Exquisite Corpse in the visual arts. A) Overhead video recording of an artist at work for a 10s sequence. B) Synchronized EEG and Acceleration data. D) Artist with measuring equipment.

6.5.1 Participants

Six professional visual artists participated in the experiment, 40-57 years old. There were two iterations of the experiment, in two groups of three.

The artists requested basic art materials such as pencils, pastels, chalk, charcoal, water-based painting materials, glue, and scissors for use during the experiment. These were provided by the researchers. The artists brought surprise materials to share among their fellow artists participating in the triad. There materials were used to inspire the sense of improvisation, collaboration, and game nature of the Exquisite Corpse among them. Examples of the surprise materials include insects, stickers, ink, film, stencils, and printed color paper.

6.5.2 Data Acquisition

EEG

Brain activity was collected with 64 active-electrode wireless EEG sampled at 1000 Hz (BrainAmpDC with actiCAP, Brain Products GmbH). The electrodes were placed in accordance with the 10–20 international system using FCz as reference and AFz as ground. Four electrodes were used for Electrooculography (EOG) recordings: two electrodes were used as horizontal EOGs placed laterally outside the eyes, and two were used for vertical EOG. The remaining 60 electrodes were used to record EEG data.

IMUs

IMUs: Three IMUs (OPAL, APDM Inc., Portland, OR) were used to track body motion data from the artists, sampled at 128 Hz. Data was collected from the head and forearms of each artist.

Video Recording

Video cameras, mounted on the walls and ceilings of the respective spaces, captured the creation of each work of art. One video camera was placed above each artist and art-work. The day after the experiment, the artists were asked to annotate the video recordings to mark significant behavioral and cognitive events.

Synchronization

The EEG, IMUs, and video data streams were synchronized with an external trigger physically connected to the EEG and IMU wireless receivers. The trigger was also connected to LEDs that were visible to all video cameras. A trigger sequence was used to indicate the start and end of the baseline conditions, and of each section of the experiment.

6.5.3 Task

Baseline conditions were taken before and after the creation of the artworks. The first baseline condition consisted of having the artists close their eyes and relax for one minute ('Baseline eyes closed (BC)'). For the second baseline condition, the artists had their eyes open, and they were asked to relax and look straight forward at the blank board in front of them for one minute ('Baseline eyes open (BO)').

The Exquisite Corpse protocol and creative outputs are shown in Fig. 6.1A and Fig. 6.1B, respectively. The protocol includes checking the impedance values of the electrodes and registering their values.

Three artists worked on a "body" consisting of three sections: head, torso, and tail/legs. The artists are provided with a pliable triboard (81 cm x 101 cm four-ply chipboard), a 2-layered panel comprised of three sections. The artists worked simultaneously on three triboards, all of them working on the head of their respective pieces for 15min: this was Section 1. After Section 1 was finished, the staff covered the artworks with a strip of cardboard, leaving approximately three centimeters uncovered at the bottom, and then transported the piece for the next artist to view before beginning the next section. The artists proceeded to work on the torso section of the artwork, continuing from the strip of information visible from the previous artist's composition: this was Section 2. Three examples of artworks created during this experiment are shown in Fig. 6.1B. The labels A1-6, correspond to artist 1 through respectively.

The protocol can be implemented across artistic modalities in the spirit of the

Exquisite Corpse [1].

6.5.4 Kinematics Data Analysis

The motion features were calculated on a 4 second sliding window with 50% overlap.

A set of 43 features were selected for data analysis: the absolute value of the acceleration (acc) (9 features) and gyroscope data (9 features) [114] from the three components of the three sensors, the acceleration magnitude (3 features), bilateral magnitude BM $= |acc_{Left}| + |acc_{Right}|$ (1 feature); logarithm of the magnitude ratio MR $= \log(|acc_{Right}|/|acc_{Left}|)$ (1 feature) [115]; and Sample Entropy [37] of the acceleration magnitude for the three sensors (3 features).

Normalized jerk has been used successfully in clinical settings [116] to characterize movement quality in stroke survivors, however, the difficulty of calculating position from the video in our experiment limits us to use only the derivative of the acceleration. The same features as in the acceleration data were calculated for the $jerk = d(acc_{component})/dt$ (17 features).

All the features used for kinematic data analysis were standardized by subtracting the mean and dividing by the standard deviation.

6.5.5 EEG Data Analysis

Quantitative neuroscience based on EEG has implemented data features in frequency band-power, time domain characteristics, and functional connectivity measures. Features in the frequency domain take the form of power in commonly used frequency bands: e.g. delta 1-4 Hz, theta 4-8 Hz, alpha 8-12 Hz, beta 12-30 Hz, gamma 30-50 Hz [23]. Time domain features involving temporal and spatial relationships between the data have been used successfully to decode movement intent in mobile settings ([19, 117, 17, 18, 33]). Connectivity features have also been used as data descriptors in EEG; such features measure the correlation or synchronization between data from two different sensors in frequency bands [27, 118].

The EEG features were calculated on a 4 second sliding window with 50% overlap. The EEG features explored were PDC for all pairs of channels, and band-power in the delta, beta, alpha, beta, and gamma frequency bands in each EEG channel.

6.5.6 EEG Data Pre-Processing

The freely-moving artists in the experiment make the EEG data susceptible to artifacts including motion-related artifacts. Electrode impedance was obtained before and after the experiment so that electrodes with impedance values above $60k\Omega$ could be removed. The EEG data was resampled from 1000 Hz to 250 Hz. The EEG data was band-pass filtered at 0.3 to 50 Hz using a 4th order zero-phase Butterworth filter. A notch filter was applied at 60 Hz to remove powerline noise. The H^{∞} ($gamma = 1.15$, $q_0 = 1 \times 10^{-10}$) filter [119] was used to remove eye-movement contamination using the horizontal and vertical EOGs as reference for eye-related signal removal. The EOG electrodes were low-pass filtered at 10 Hz before running the H^{∞} filter. Then we used Artifact Subspace Reconstruction [120] to remove bursts of abnormal activity, and we used interpolated channels that were removed due to excessive noise, using spherical interpolation. We ran Independent Component Analysis to remove additional artifacts.

6.5.7 Classical Machine Learning

6.5.8 Feature Selection

The most relevant features across subjects were selected using a mutual information implementation of the mRMR [42] algorithm. In mRMR, a feature score is sequentially calculated by computing the mutual information between each feature and the target/class vector; and subtracting the redundancy term: average mutual information between each remaining feature and the previous selected features.

6.5.9 Classification

The classical machine learning classifier used for the EEG and motion data was the kernel support vector machine (kSVM), using the polynomial kernel of degree 3. The value of the and box-constraint was set to 1 in all cases.

Classical machine learning techniques involve a combination of hand-crafted features, based on previous neuroscience, to approach the problem. These features are then set as input for a classifier. We used band power features for each channel and PDC between all channel pair combinations as features, in 4s windows with 25% overlap. The features obtained in each of these data windows constitutes constitute a data sample. The data samples from all subjects were analyzed together. We selected randomly, with repetition, $N_s = 500$ samples per class, to achieve class balance.

The training, validation, and test sets were by temporal subsampling. The data from the first temporal 80% of the experiment was selected for the training and validation sets, while the last temporal 20% was selected for the test set. From those samples, ($N_s = 500$) samples were selected to achieve class balance, divided into

($N_s = 400$) samples for the training and validation sets, and ($N_s = 100$) for the test set.

6.5.10 EEG Automatic Feature Extraction through CNNs

Automatic feature extraction algorithms offer a promising approach to study the neural basis of a complex cognitive task such as the human creative process across demographics, styles, and artistic domains. Automatic feature selection algorithms have shown rapid progress in recent years applied to EEG data [50, 44].

The proposed CNN architecture (Fig. 6.9) for the purpose of this report is a 6-layer architecture with one temporal convolutional layer and one spatial convolutional layer. We aim to resemble typical EEG feature extraction strategies [23]: frequency bank information in a temporal convolution, followed by spatial combinations of electrodes (such as in ICA, PCA, etc) [50] through a spatial convolution. The temporal layer aims to extract temporal and frequency-related information from the EEG signals, for each channel separately, projecting to a number of filters. Then, a spatial convolution combines the information from all of the channels at each time point, and projects it down the CNN layers. A Max Pooling and a Fully connected layer, with 20% dropout for stochastic robustness, lead up to the Fully Connected Softmax Classification layer.

The hyper-parameters were optimized for highest average classification results in the test set: number of temporal filters $H_1 = 2$, length for time convolution $H_2 = 75$, spatial filters $H_3 = 10$, nodes in fully connected layer $H_4 = 40$, and the learning rate $H_5 = 0.00075$. See Fig. 6.9 for a schematic representation of the CNN architecture used.

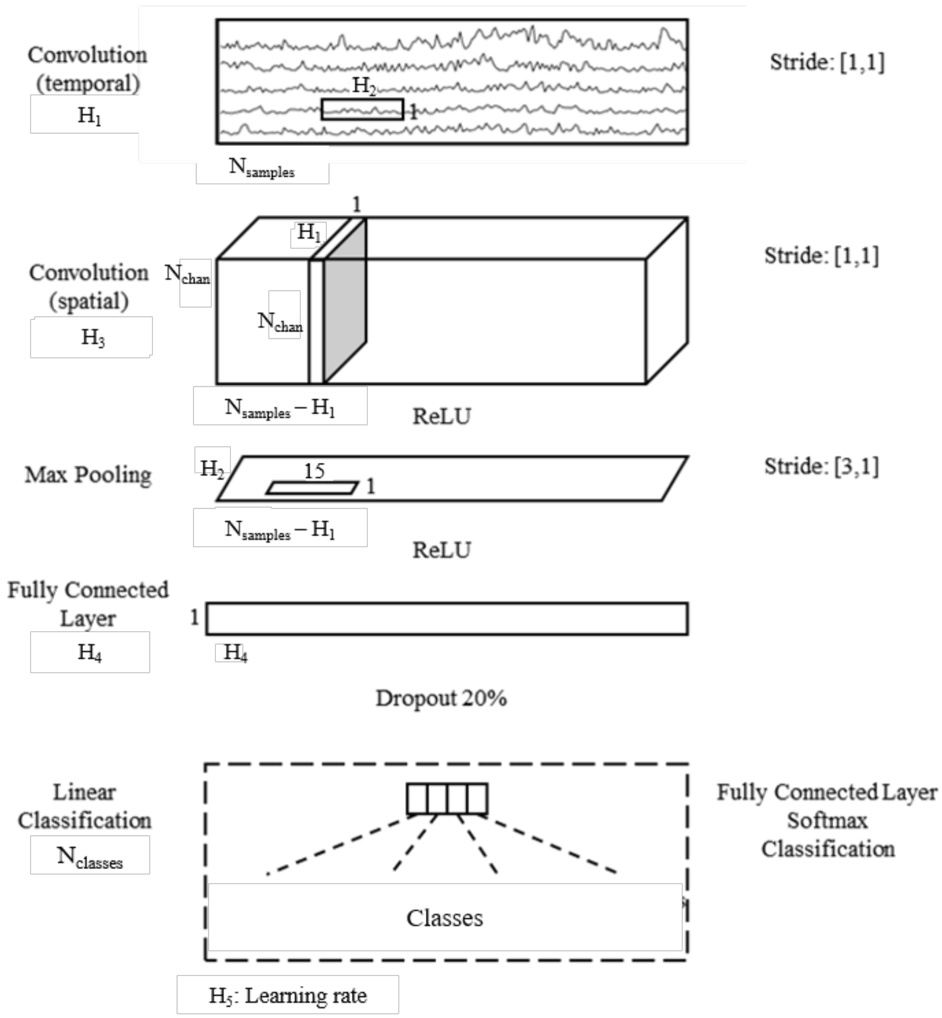

Figure 6.9: CNN Architecture. Hyper-parameters: temporal filters $H_1 = 2$, length for time convolution $H_2 = 75$, spatial filters $H_3 = 10$, nodes in fully connected layer $H_4 = 40$, and the learning rate $H_5 = 0.00075$.

6.6 Author Contributions Statement

JGCG collected the data (with help from the staff and students from the Laboratory for Noninvasive Brain-Machine Interface Systems), performed the data analysis, and wrote the first draft of the manuscript. JGCG, DR, and JLCV designed the experiments. DR and JLCV conceived the research. All authors wrote the manuscript. All authors reviewed the manuscript.

Chapter 7

Characterizing the stages of creative writing from frontal and temporal mobile EEG data using Partial Directed Coherence: Pilot Study

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Bibliographic information: [1]

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7.1 Abstract

The development of mobile brain-body imaging technology provides the opportunity to study the human creative process outside of constrained laboratory settings. In this study, we used portable dry EEG systems (four channels: TP09, AF07, AF08, TP10, with reference at Fpz), coupled with video cameras, to record the brain activity of Spanish heritage students as they developed their creative writing skills over four months enrolled in an undergraduate course on creative writing in Spanish. The students recorded their own brain activity as they walked through and experienced areas in the city (Preparation phase), and while they worked on their creative texts (Generation phase). We measured Partial Directed Coherence (PDC) between the Preparation and Generation phases of their work. There was higher PDC in the Preparation Phase at a significance level of $p < 0.05$, from TP10 to AF7 among all frequency bands analyzed: 1-50 Hz. The opposite directionality was found for the Generation phase, in frequency bands: 13-50 Hz. Information transfer from temporal-parietal to anterior-frontal areas of the scalp may reflect sensory interpretation during the Preparation phase, while high frequency bands PDC directionality originating at the anterior-frontal areas during the Generation Phase may reflect the final decision making process to translate the sensory experience into a tangible product: text.

7.2 Introduction

Writing involves embodied practices that physically connect us with our surroundings [98]. We investigated creative writing as a bodily experience, in which the author's interaction with the world around them (physically, verbally, etc.) informs the cultivation and elaboration of their work. In this way, as an author engages in actively experiencing the world around them through their body, they may seek to achieve an aesthetic effect to aim for in their creative production.

We integrated wearable MoBI technology into a creative writing course in Spanish, designed after the idea of approaching creative writing as a bodily experience. In the class, a creative writing professional served as the class instructor and relayed her creative methods on a creative writing workshop for 18 non-expert heritage Spanish speaking students. Bringing the artist early into the planning of the study provided an equal consideration in the experimental design and evaluation process to best assess the creative process in a minimally intrusive way.

We studied the process of creative writing on non-expert Spanish heritage speakers, as they engaged in the Preparation and Generation phases of their writing. The students were asked to walk through different areas of the city and experience their environment in a variety of settings, and use the experience to create an aesthetic effect in their texts. The exact writing prompts are shown in the Supplementary Materials. This study aimed to identify EEG features related to the different stages of a creative writing task where subjects were able to move, explore their surroundings to inform their creative texts (Preparation Phase), and write at their own time (Generation Phase). The EEG features explored were PDC, sample entropy, and band-power in the delta, beta, alpha, beta, and gamma bands.

This is the first study investigating the neural features associated with creative writing using quantitative EEG metrics to compare different phases of the process (i.e., Preparation, Generation). See Table 7.1 for a landscape on the neuroscience literature in creative writing. Tables 10.3 and 10.3 summarize the literature outlined in Table 7.1.

Table 7.1: Neuroscience literature where the task involved creative writing as an experimental task.

		fMRI		qEEG	
		Functional Connectivity	Activation	Coherence	Band Power
Resting-state vs creativity level	Martindale & Hasenfus, 1978				Qualitative
	Jausovec, 2000.				
	Jausovec & Jausovec, 2000.				
	Takeuchi et al., 2012.*				
	Wei et al., 2014.*				
	Lotze et al., 2014.				
	Sun et al., 2018*				
Stages of creative process	Howard-Jones et al. 2004.				
	Shah et al., 2013.				
	Erhard et al., 2014.				
	Liu et al. 2015.				
	Cruz-Garza 2019 (this report).				

7.2.1 Neuroscience of the Creative Writing Process

Coherence metrics between pairs of EEG electrodes or brain regions have been used to identify differences in resting-state brain dynamics and correlated significantly with an individual's creativity level [121, 122, 101]. Alpha power in frontal, central, and parietal locations has been consistently found to be modulated in relation to creative task demands, to increase in relation to an individual's creative level, and to increase after performing a cognitive creative problem solving task [14].

Using fMRI to measure functional connectivity (FC) of subjects at rest, the resting state FC (rFC) between medial prefrontal cortex (mPFC) and the posterior cingulate cortex (PCC) [123] and medial temporal gyrus (mTG) [124] has been found to correlate positively with the individual's performance in creative problem solving tests. Lotze et al. [125] found decreased rFC between inter-hemispheric areas BA 44, and left area BA 44 with the left temporal lobe for individuals who scored higher in a verbal creativity index test.

Moving past analyzing resting state brain dynamics, recent fMRI studies have analyzed the human creative process through its distinct stages of preparation, generation, and revision. Shah et al. [126] studied the Preparation and Generation phases, finding distinct cortical networks associated with each. Erhard et al. [102] found that experts had higher activation in prefrontal and basal ganglia areas. Liu et al. [60] studied the generation and revision phases. They found that the mPFC was active during both phases and the responses in DLPFC and Intraparietal sulcus (IPS) were deactivated during the Generation Phase.

Although, fMRI studies report involvement of the mPFC, and phase-dependent and creative level-dependent activation of DLPFC, IPS, PCC, and basal ganglia, differences in brain activity for the distinct stages of the creative process remain mostly unexplored in the EEG domain; particularly for creative writing tasks. Table 2 summarizes the approaches that neuroscience studies have taken to study the creative process in creative writing.

There is a clear gap in the neuroscience of the human creative process in the use of quantitative EEG (qEEG) used to analyze the stages of the creative process. Mobile EEG allows for the collection of brain activity data in more natural settings, where the users have free range of motion and translation. We propose to study the human creative process in creative writing skills as the subjects are free (and encouraged) to explore their environment to build on the ideation / Preparation stage, as well as on the Generation Phase of the process.

7.3 Methods

Through readings and writing prompts, non-expert creative writing students were asked to acknowledge the physicality of the writing process and to relate it to the materiality of language. Prompts issued in the upper-division undergraduate workshop

(SPAN 3308 YOUR BRAIN ON WRITING: Writing, Body, and Neuroaesthetics) where the EEG data was obtained encouraged students to develop and record a series of specific writing preparation tasks (walking, running, climbing in different locations of Houston) as they completed the first Phase of required assignments. Students also wore head devices as they sat down and completed their creative texts. The writing prompts are provided in the Supplementary Materials.

7.3.1 Task

Eighteen non-experts, heritage Spanish speakers, participated in a Spanish language creative writing workshop at the University of Houston. Anonymous Informed Consent was approved by the University of Houston Institutional Review Board. The participants provided Anonymous Informed Consent at the beginning of the workshop. They were trained to set up their own EEG headsets and body-mounted video cameras for the experiment. The participants were responsible for the collection of EEG data, video, and to keep a diary with notes on each recording session.

The participants were asked to walk around the city in a variety of locations, and to use their experience to generate their creative texts , constrained only by a 3-5 page length suggestion (double space, 11 point font) . The participants were instructed to use the EEG and video cameras during their walking activities and writing time. There could be more than one session of walking and writing times per prompt.

This experimental setup produced data in two phases of the creative process: the Preparation Phase and the Generation Phase. The Preparation Phase involved tasks such as walking, active observation of their environment, taking notes, and ideation. For the Generation Phase, the task involved reviewing their notes and typing their texts into a complete creative piece, with iterative revisions and modifications.

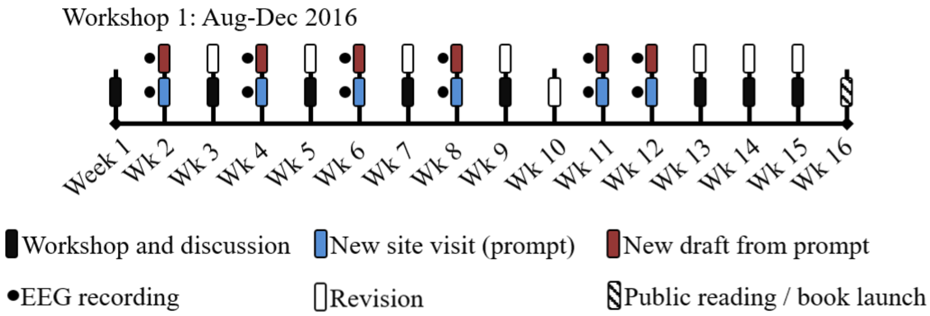

Figure 7.1: Creative Writing workshop 1. Pilot study. Timeline for the EEG recording sessions in the creative writing workshop: talleres de escrituras.

7.3.2 Measurement Equipment

EEG and head acceleration data was captured using Muse headsets (Interaxon, Toronto, Ontario, Canada). The headset has seven sensors, two out of these seven sensors were positioned at the frontal region (AF07 and AF08), two at temporal-parietal region (TP09 and TP10), and the remaining three sensors served as electrical reference located at the center of the forehead (Fpz). The headset has an inbuilt accelerometer that was used to measure the head acceleration. EEG data for each channel were measured in microvolts with sampling rate of 220 Hz. The acceleration data was recorded at 50 Hz. Additionally, the data recordings contain a vector indicating contact quality for each electrode sampled at 10 Hz, rating contact quality as "indicator $= 1$: good", "indicator $= 2$: Ok", "indicator ≥ 3: bad".

The participants set up their own headset with a custom application given to them in a personal tablet, which recorded EEG and head acceleration data and labeled the subject identification number and date/time for the recording session automatically. The data recording setup is illustrated in Fig. 7.2. Additionally, the participants set up body-cameras (Conbrov, ShenZhen, China) to record their exploration (Preparation) and writing (Generation) sessions. The camera recorded

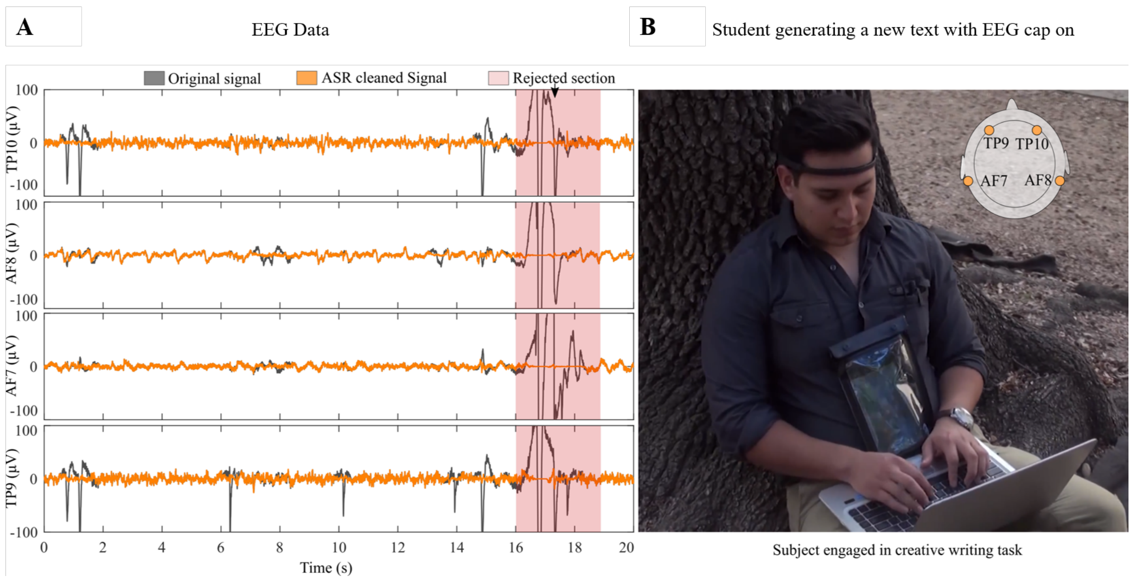

Figure 7.2: Equipment setup and EEG data pre-processing. A) Raw (black) and pre-processed (orange) EEG data. Shaded areas indicate rejected intervals. B) A student wearing the EEG headset during the Generation Phase.

720 HD video on a 75° wide-angle lens.

7.3.3 Data Collection

Eighteen students participated in the study. The students were asked to make five writing exercises and collect their brain activity as they walked and observed their environment (Preparation phase), and created their texts (Generation phase). Only writing assignments that were submitted and accompanied by both video and EEG data were considered for the analysis. From the eighteen initial subjects, data from eleven subjects was discarded due to incomplete data (video or EEG missing) or assignments not submitted on time.

The Preparation and Generation phases for each writing exercise were done in several distinct recording sessions as each Phase could take several time-separated recording sessions to compete. We kept each data recording as a separate session to analyze. Recording sessions were considered for analysis when all 4 electrodes had a "good" contact indicator for at least one continuous minute of data.

7.3.4 Pre-Processing

Data recordings with both video (context) and EEG were considered for this analysis.

An online notch filter was applied on the EEG data to remove the 60 Hz power line noise. We applied an offline 4th order, zero-Phase Butterworth band-pass filter from 1 to 100 Hz. Artifact Subspace Reconstruction (ASR) [120] was used for the removal of short-time high-amplitude artifacts in the continuous data. Calibration data for each individual subject was computed from the entire length of the trial using automated methods. A cut off threshold of ten standard deviations was used for the identification of corrupted subspaces, and a window length of 500 milliseconds with a step size of 250 milliseconds was used for the ASR. Among the segments, channels having corrupt PC loading to be greater than 0.75 were removed. The remaining segments were then inspected automatically to remove data from any electrode disconnections from the scalp (tracked by the headband status data), any abrupt change of voltage greater than 100 μV, or EEG data collected while there was an absolute acceleration magnitude larger than 1 ms^{-2}. A complete flowchart for the aforementioned data pre-processing and de-noising is shown in Fig. 7.3.

7.3.5 Feature Extraction

The PDC was computed for all pairs of electrodes in the frequency bands: delta [1-4 Hz], theta [4-8 Hz], alpha [8-12 Hz], beta [12-30 Hz], gamma [30-50 Hz].

The data was re-segmented into 2s windows with 1s overlap. The power spectral

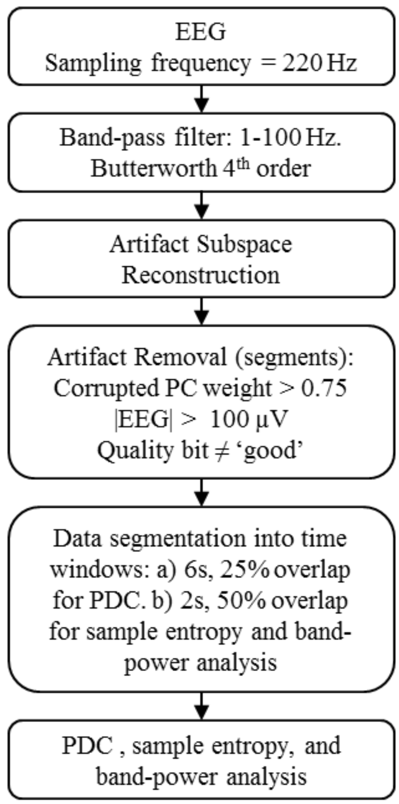

Figure 7.3: EEG data pre-processing and feature extraction. Flowchart for EEG data pre-processing and de-noising. The ASR and artifact removal were done on 500ms windows of data with 250ms overlap.

density (PSD) was computed for each window of 2s using Thomson's multitaper PSD estimate in Matlab, with 50 frequency bins [1-50 Hz] and half-bandwidth product nw = 4. Relative band power, given by the sum of the power in each band-related frequency bin, divided by the total power 1-50 Hz, was computed for the EEG data in each time window.

The median value of the relative band power was computed for the Generation and Preparation phases. The percentage change in band-power between the Generation and Preparation phases, which we call "Relative median power change" (ΔmBP), was computed using the following equation:

Relative median power change:

$$\Delta\mathrm{mBP} = [(\mathrm{median}(BP_{gen}) - \mathrm{median}(BP_{prep})]/\mathrm{median}(BP_{gen}) \,, \qquad (7.1)$$

where ΔmBP is the change in median band power, BP_{gen} is the band power in the Generation Phase, and BP_{prep} is the band power in the Preparation Phase.

The 6s windows with 1s overlap data was used for sample entropy analysis.

In this study, $m = 2$ and $r = 0.2\sigma$, where here σ is the standard deviation of the signal window, and $N = 440$ (2s of data sampled at 220 Hz).

7.4 Results

The PDC between the Preparation and Generation of creative writing has opposite directionality between right temporal and left anterior frontal area. Fig. 7.4 illustrates the results for the connectivity between electrodes, using PDC, during the two stages of the creative writing process analyzed.

Preparation Phase: There was higher PDC in the Preparation Phase originating from TP10 towards AF7. The PDC difference between the Preparation and the Generation phases were statistically significant at a confidence level of p <0.05 for the frequency bands delta, theta, alpha, beta, and gamma. Fig. 7.4 shows the PDC scores, bounded between 0 and 1, for all pairs of electrodes.

Generation Phase: There was higher Partial Directed Coherence in the Generation Phase originating from AF7 towards TP10. The PDC difference between the Preparation and the Generation phases were statistically significant at a confidence level of $p<0.05$ for the frequency bands beta and gamma.

The statistical difference in PDC and its opposite directionality when comparing the Preparation and the Generation Phases indicates that there was a strong relation between the left anterior frontal with the right temporal-parietal areas when the students engaged in the tasks.

There were no statistical differences, at a significance level of 5%, between the tasks "Preparation" and "Generation" for creative writing in this experiment (Fig. 7.5). There was, however, higher median beta and gamma power during the Generation phase, as well as alpha suppression (TP9, AF8) during the Preparation Phase.

7.5 Discussion

The higher coherence values from the right temporal towards the left anterior frontal electrode during the Preparation phase, is potentially associated with the processing of sensory input [127, 128] and episodic emotional memory retrieval [129, 130, 131] in the temporal lobe as subjects explore their surroundings actively engaging the frontal cortex in integrating the experience. The opposite directionality between the same electrodes (Fig. 7.4) reinforces this hypothesis in which processed input in the frontal areas is related back to sensory processes.

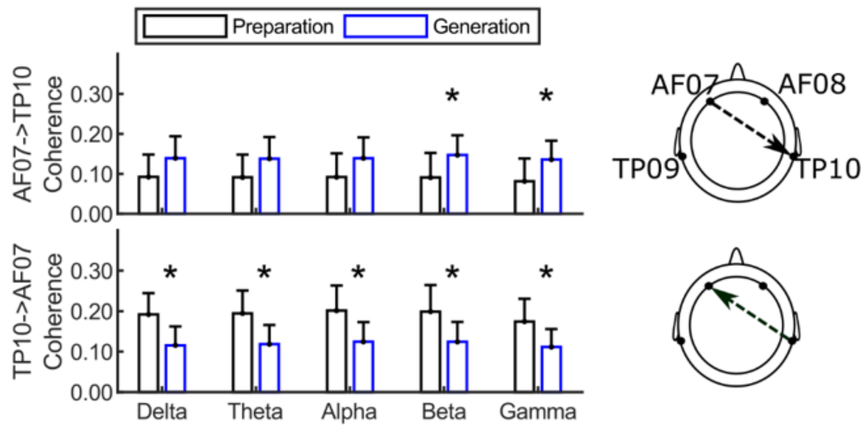

Figure 7.4: PDC for the Preparation and Generation phases. Higher PDC in the Preparation Phase, from TP10 to AF7, for 1-50 Hz. Opposite directionality in the Generation phase, for 13-50 Hz.

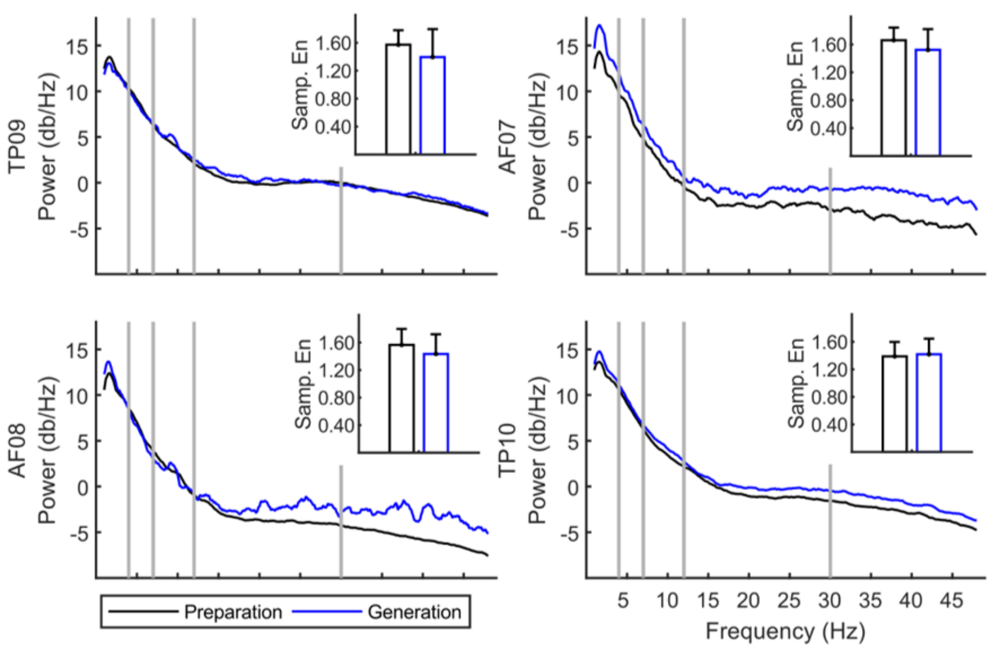

Figure 7.5: Power spectrum (median) and Sample Entropy for the Preparation and Generation phases. No significant differences were found.

Our results, although constrained to frontal and temporal recording locations, relate to previous findings in fMRI studies analyzing the different stages of the creative process. There are distinct cortical networks associated with each Phase. Shah et al. [126] identified ventrolateral prefrontal cortex activation during the Preparation phase, and central-parietal areas involved in the Ceneration Phase. "Brainstorming" engaged cognitive, linguistic, and creative functions represented in a parieto-frontal-temporal network, while "Creative writing" activated motor, visual, a cognitive and linguistic areas mainly over central and parietal networks [126]. Liu et al. [60] found that the mPFC was active during the generation and revision phases. They confirmed deactivation of the DLPFC and IPS during the Generation Phase.

Our results show higher coherence values from the right temporal towards the left anterior frontal electrode during the Preparation Phase for all frequency bands analyzed (1-50 Hz); and the opposite directionality for the Generation Phase in higher frequencies (13-50 Hz). We did not find statistical differences between the Preparation and the Generation phases for Sample Entropy of frequency band power.

Overall, these findings suggest that ideation, exploration, and observation during the Preparation Phase of a creative writing task can be characterized by a state of long-range cortico-cortical communication between multisensory integration brain areas (temporal regions) and high-order execution and planning areas of the brain (prefrontal regions), perhaps leading to selective storage of ideas, concepts or observations candidate for creating writing during the generation Phase. We hypothesize this focal activity may be related to working memory, sequence production, and processing of filtered information from the Preparation Phase.

7.6 Acknowledgements

This research was funded in part by NSF award #BCS1533691, NSF IUCRC BRAIN Award CNS1650536, a Seed Grant from the Cullen College of Engineering at the University of Houston, and the SeFAC grant from the Center for Advanced Computing and Data Science (CACDS) at the University of Houston.

7.7 Author Contributions Statement

JGCG performed the data analysis wrote the manuscript. ASR prepared and pre-processed the data, and pefromed preliminary analysis. AEK assisted students on a weekly basis on data collection, and compiled the multimodal data in a working dataset. JGCG, AEK, and CRG planned the experiment. CRG conducted the workshop. JLC-V and CRG conceived the research and edited the manuscript. All authors reviewed the manuscript.

Chapter 8

Embodied writing: Understanding neural dynamics during creative writing

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8.1 Abstract

Creative writing involves embodied practices that physically connect us with our surroundings and our community through our bodies' interaction with them. In a unique collaboration at the nexus of the humanities and neural engineering, we investigated the neural dynamics of heritage bilingual students before and after a 14-weeks creative writing workshop led by Prof. Rivera Garza.

The students composed creative texts and a text transcription while wearing

[1]To be submitted as a journal article in 2019-2020. The chapter organization is based on the template from the journal Scientific Reports.

active-electrode scalp electroencephalography (EEG) caps. As result of the workshop, the students used less adjectives, and more questions and reflections in the session after the workshop. In regard to brain activity, we found a significant increase in cortico-cortical communication, as assessed by partial directed coherence, between right occipital and left central-frontal electrodes indicating a dynamic cognitive visuo-motor neural network engaged during creative writing and understanding. This finding was observed in both the transcription and creative writing conditions. Additionally, in the transcription condition, we also observed desynchronization in the frontal and central-frontal scalp electrodes in the delta (0.3-4 Hz) band. Writing is the taking of decisions, a means for reflection and the sharing of such reflection through the written actions; and transcription shows the same changes in information transfer after the 14-week workshop than the creative writing conditions: transcription is an active intellectual, emotional, and social endeavour. Sharing texts, practices, and experiences through a creative writing workshop created physiological changes in how the brain processes and transforms information from visual and motor experiences into written language.

8.2 Introduction

Creative writing involves embodied practices that physically connect us with our surroundings and our community through our bodies' interaction with them. Previous electroencephalography (EEG) studies pertaining to creative writing, have reported that highly creative individuals exhibit higher alpha power during creative inspiration (preparation) than creative elaboration (generation); which was not found in less creative subjects [98]. In another study, as participants thought about writing an essay, more creative individuals (based on their "creativity scores" assessed by the Torrence tests) showed higher coherence across the scalp, in the alpha (8-12 Hz) band [101]. Moreover, alpha power in frontal, central, and parietal locations has been consistently found to be modulated in relation to creative task demands, to increase in relation to an individual's creative level, and to increase after performing a cognitive creative problem solving task [14].

Erhard et al. [102] and Liu et al. [60] have proposed working models for the human creative process based mainly on neuroimaging and behavioral experiments conducted in laboratory settings. They found dorsolateral prefrontal cortex (DLPFC) deactivation during creative production, and activation during text revision. Although these studies provide valuable insights into the nature of the human creative process, unfortunately, they leave the question of effects of environmental context and the free and embodied nature of behavior, unresolved as the experimental setting is carried out inside the confines of the scanner room, far from natural contextual settings in which free-behaving individuals usually create. Fink and Benedek [14] discuss the role of alpha power in creative ideation measured with EEG, as it increases during creative task performance or as a function of the individual's creativity level. Alpha power was found to be among the among the most consistent finding among studies.

To study the neural dynamics associated with the creative writing experience, we assayed the brain activity of eight bilingual upper division college students before and after they participated in a semester long creative writing workshop at the University of Houston (SPAN3311 WRITING HOUSTON: Writing the Second Ward). The purpose of the workshop was to critically examine the relationship between body and writing.

The workshop was created by Prof. Cristina Rivera Garza, based on her theoretical work on creative writing as an embodied processs[98]. The workshop connected Spanish heritage speakers and English speaking students to the practice of writing as a bodily experience and community-making practice. This class provided the students with neuro-technology with the aim of enhancing their visualization and understanding of their body's experiences as they explored the Second Ward, a historically Hispanic neighborhood in the heart of Houston. Leveraging the values of the University of Houston, a Hispanic serving institution, we empowered students by enabling them to use cutting edge technology to inform their writing and provide them with the tools to engage in the emerging field of Digital Humanities.

Our goals for the class were threefold.

1) First, students would be able to connect writing and community in unique ways. As they walk through Second Ward, paying attention to flora and fauna, buildings and houses, or conducting interviews with dwellers and/or artists, students will gain intellectual and experiential knowledge about one of the most traditional neighborhoods in east downtown Houston. They would learn that writing is a community-making practice [98].

2) Interdisciplinary collaboration with students from Graphic Design would result in the making of a published book— giving back a tangible text to the community where the experiences came from, and to connect the university with communities from the area.

3) The MoBI team would work together with experts in the field of creative writing to measure brain activity and characterize the creative writing process in terms of neuroscience; both before the 14-week workshop and after the workshop. This data may allow us to measure cortical correlates of improvement in creative writing skills over the course of the semester, as well as awareness of the students' bodies and surroundings in the implementation of their writing skills.

Cognitive processes are often based on the surrounding environment and our own physical body [132]. The contextual setting of the subject has implications in both perceptual and motor processing. We aimed to uncover the neural correlates associated to those perceptual and motor processing information and how they relate to the embodied writing experience: how do EEG data features are progress with creative writing training as an embodied experience, and how do these relate to current philosophy of creative writing practice?

8.2.1 Description of the Creative Writing Workshop

We integrated EEG technology into a creative writing workshop. During the workshop the students physically experienced the writing prompts (locations in Houston), and their community. The students wrote creative texts from the prompts visited. Those texts were discussed as a group during workshop hours. Two of those discussion sessions were equipped with EEG recording [2]. Finally, at the end of the workshop, the students went through the same creative writing prompts again, now with bodily experience in those locations. This chapter analyzes the change in neural features from Before and After the workshop using the writing prompts. Only the writing sessions Before and After the experience of the workshop are discussed here.

Specifically, we studied the process of creative writing on non-expert writers, as they engaged in the generation of improvisational creative writing tasks based on prompts: pictures of locations in the Houston Second Ward. Students wrote the Second Ward— a historically Mexican neighborhood in the heart of Houston and only a couple of kilometers away from the University of Houston main campus.

During the workshop, the students and the instructors discussed a range of strategies for urban writing, and cross-genre ('trans-género') writing. The students also analyzed writing strategies through readings and interactive writing tools. Crucially,

[2] The in-class workshop sessions are not discussed in this report.

the students took three walking tours throughout the Second Ward focusing on language, botany, community, social history, and graffiti art. Each walking tour was led by experts in the field. Commenting and revising these three tours and writing prompts was the core of this course, discussed in two to three workshop sessions afterwards. At the end of the course, the students were asked to create a 10-page long piece of cross-genre writing to be published together in a community book in partnership with graduate students from Graphic Design.

Students in this hands-on writing workshop took three walking tours throughout the Second Ward — a historically Mexican neighborhood in the heart of Houston — focusing on language and botany, social history, and graffiti art. Each walking tour was led by experts in the field and paired with a writing prompt (e.g., specific locations and communities). Commenting and revising these writing prompts was at the core of this course. Based on revised work, students wrote a 7 to 10-page long piece of cross-genre writing by the end of the semester.

Overall, the goal of this course-study was two-fold. From the pedagogical perspective [98], we wanted to show students that writing is a community-making practice, that is, we aimed to teach students how to learn to connect writing and community in unique ways, while gaining intellectual and experiential knowledge about one of the most traditional neighborhoods in east downtown Houston. From the neuroengineering perspective, we aimed to interrogate the neural dynamics of the students' creative brain in action in a natural ecologically valid setting. To achieve this aim, 32 channel active electrode EEG (BrainAmpDC with actiCAP, Brain Products GmbH) data was acquired at 1000 Hz, while the students wrote creative essays in two time-constrained creative writing sessions: one before the workshop (week 1); and one after the workshop (week 14).

During these creative writing sessions, the students were given three writing prompts (2min each), preceded with periods of rest with eyes open (1min) and eyes closed (1min), and a control condition where they transcribed a text (2min). We expected the brain dynamics to change as a result of the writing workshop. Specifically, to assess the effective brain networks during the creative writing tasks before and after the workshop, we used the partial directed coherence (PDC) analysis [27], based on Granger causality (GC) [133]. PDC allowed for the examination of the flow of directional information of the instantaneous interactions of the brain among several electrodes.

8.2.2 Task

In this work, eight bilingual students participated in a creative writing workshop over the course of a semester. This experiment analyzed the effect of an intervention on training individuals and concomitant neural changes on improvisational creative writing performance. The students wrote creative texts while wearing the EEG equipment in two time-constrained creative writing sessions: one before the workshop, in week 1; and one after the workshop, in week 14.

During the time-constrained improvisational creative writing sessions, the students were given three writing prompts (2min each), preceded with periods of baseline with eyes open (1min), baseline eyes closed (1min), and a control condition where they transcribed a text (2min).

The students' end goal was to produce a published book in community. The workshop, therefore, provided the students with skill development through theory, readings, and examples, and by experiencing the embodiment of the creative writing process (visiting the locations), making drafts, discussing them, and editing a published book as a final product.

8.2.3 Transdisciplinary Hypothesis Generation

Formal learning in creative writing paired with experiential Informal STEM Learning with MoBI technology enabled students to gain knowledge about how their brain processes information during writing-related activities; from the gathering of sensory and memory data to the writing, reflecting, and marking creatively their lived experiences. Writing not as a random result of inspiration, but as a process that can be cultivated and augmented through experiences. We hypothesize that neural markers associated with the creative process will be uncovered, providing insight into the neural mechanisms involved in writing, current writing philosophy-writing as an embodied experience, and neural dynamics associated to creative writing performance and understanding.

Provoked by the EEG recording devices, this class created a conscious relationship between body, mind, brain, and language, providing physiological data to help students to understand creativity and writing. It is a class that immerses the students in a learning experience through body and community: they learn together, physically experience the Houston Second Ward together; they write and discuss their texts together in a transdisciplinary context.

This transdisciplinary collaboration provide underrepresented communities of students with an emerging tool for learning and experiencing their bodies. It is our goal to empower Spanish heritage speakers at the University of Houston to pursue experimentation, creativity and learning as heritage speakers, students, community members, and writers.

We analyzed the number of adjectives used in the creative writing tasks before and after the workshop. Without the physical experience and the community engagement from visiting the prompts, we expect the students to use adjectives to describe settings and situations related to the creative writing prompts. After the workshop, we expected more references to the body, introspection, and reflection based on their lived experience. Similarly, we expected to find neural features associated to the cognitive processes involved in their creative writing experiences: activation of parietal (spatial planning), temporal (sensory processing), and frontal regions (executive function and information assimilation) to be more active at the end of the workshop during improvisational writing tasks.

We expected that as the students' creative writing skill develops, the neural features related to the creative writing process will be accentuated in the after-intervention experiment session. Central and parietal areas would become involved from the use of memory (after interacting with the locations used as stimulus), spatial planning for their compositions, and increased involvement in theta band with periodic modulation (spatial navigation and recollection) [103]. The involvement of these cortical areas would take the form of changes in information transfer between parietal and frontal regions of the brain, as the students associate sensory experience, and memory, with the prompts, after the workshop. They would also have more writing strategies to produce experiential evocative language and reflection when writing after the workshop. In particular, as the alpha band has been consistently found to be involved in creative performance [14], we expected to find alpha desynchronization in motor (executive function) areas, modulating central and parietal alpha desyncrhonization [1].

The experiment includes a transcription (copying a text) control condition from which to compare creative writing texts with. In the creative writing production tasks, we expect the students to use writing strategies related to the prompt shown. However, we the transcription task is also not just a mechanical action: reading and copying a text is an intellectual and emotional reproduction of a material that is itself creative. Students would be able to identify poetic mechanisms that the transcribed text uses to evoke an experience, which would be accentuated after the creative writing workshop. Therefore, we expect similar cortical features to be found relevant both in the transcription and the creative writing conditions; however, we expect more pronounced changes in frontal alpha band power and information transfer in the creative writing conditions, as students actively seek to use those strategies to create new material.

We aim to develop a predictive model of brain dynamics associated to the process of creative writing composition though mobile brain-body imaging. This model could have transformative impact on promoting and assessing creative skill development, personalized education and innovation.

8.3 Results

The text analysis results based on the frequency of adjectives and questions observed in the produced texts before and after the creative writing workshop, and physically interacting with the spaces in the prompts (Fig. 8.1).

A visual representation of the most discriminant EEG features per class is shown in Fig. 8.2 for band power analysis and Fig. 8.3 for Partial Directed Coherence (PDC) analysis. The features plotted are those which showed significant statistical differences from Baseline Eyes Open, at a significance level of 5% for the band power features, and at 0.1% for the PDC features. These figures show the results for the band power and PDC features before and after the workshop. We analyzed six tasks: A rest condition as Baseline with Open (BO), Baseline with eyes closed (BC), Transcription of a text (Tr), and three create writing texts (CW1, CW2, and CW3) respectively.

8.3.1 Text Analysis Results

The creative writing workshop provided the students with the experience of physically visiting the spaces described in the prompts and understand them in relation to their community, their history, and their bodies as a response to the space. Fig. 8.1 shows the distribution of six features compared between texts created before and after the creative writing workshop in response to the three prompts. The features compared were: Number of adjectives, number of questions or doubts or chiaroscuros, number of nouns, number of place-related nouns, number of body-senses-related nouns, and number of time-related nouns.

The number of adjectives used significantly decreased after the workshop, while the number of questions and doubts expressed in the texts increased significantly after the workshop. Before the workshop, there was an effort to describe the places through representation of reality. After the workshop, there was an effort for the use of the evocative capacity of language on topics such as the body, society, and the space itself. Concrete questions and doubts expressed in the text reveal a process of reflection upon writing, and an effort to portray those reflections in a variety of literary strategies.

There was not a statistically significant change in the use of Nouns before and after the workshop. However, there was a significant increase in the use of nouns referring to bodily-senses and those related to time.

These changes, a reduced use of adjectives per word and an increase use of nouns related to body and time, are indicative of the strategies used by the students after physically experiencing the writing prompt locations and completing the creative writing workshop. They rely less on descriptive words to construct a creative text; rather, they question the space through writing and they implement physical relations

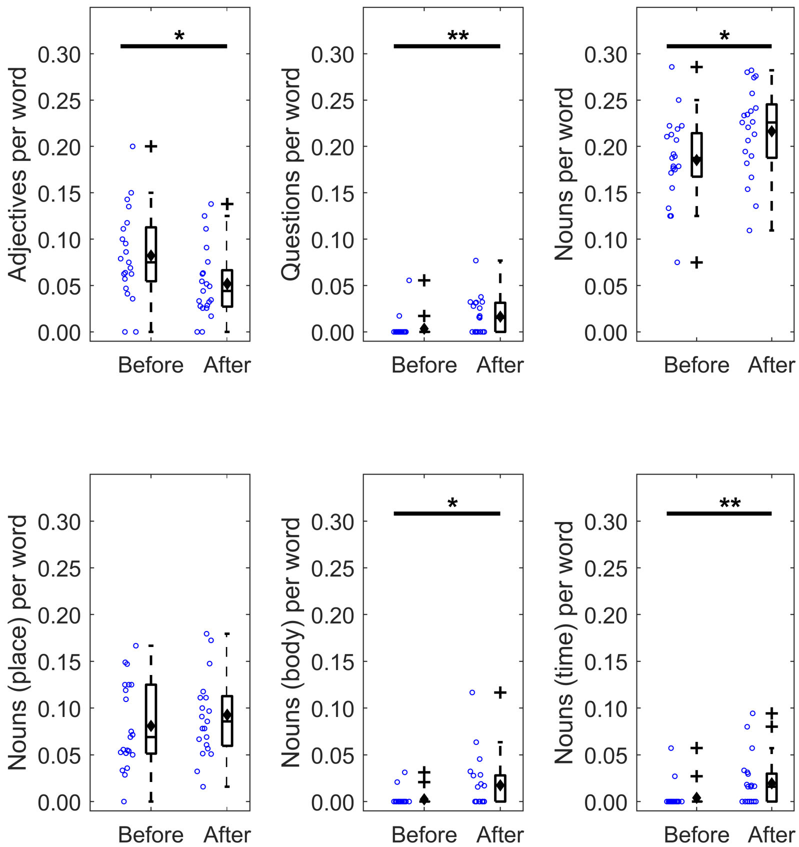

Figure 8.1: Text comparison before and after the creative writing workshop. 21 creative texts per box plot: seven students provided each three creative texts. $p < 0.05$: *; $p < 0.01$: **.

to their bodies and a sense of time into their texts.

8.3.2 Band Power Analysis in EEG Features

The band power features shown in Fig. 8.2 provide a information about synchronization and desynchronization of neural activity over brain areas involved in the human creative process.

In the Transcription condition, there is a clear desynchronization (less power) in the frontal and central-frontal regions for the delta band (1-4 Hz). This is is seen both before and after the workshop. There is occipital synchronization in the gamma band (30-50 Hz), and desyncrhonization in central regions in the alpha band.

In the CW1-3 conditions, the band power patterns are consistent throughout; suggesting that the neural dynamics are similar for the creative writing conditions, as expected. In the delta and gamma bands, there is power increase in occipital regions, both before and after the workshop. In the alpha band, there is clear desynchronization in the central regions, which is much more pronounced in the session after the workshop. The beta and gamma bands show more power parietal - occipital regions in the session after the workshop.

8.3.3 PDC Analysis in EEG Features

The PDC features shown in Fig. 8.3 provide deeper insights into the flow of information between electrode locations over the scalp. There is a clear difference in the PDC connection strength during the session after the creative writing workshop. Among all frequency bands, there is higher PDC from right parietal regions to central channels, as well as lower PDC from frontal to central channels.

This finding is consistent across all three creative writing conditions, and across students: five out of six students show this pattern (See Supplementary Materials Fig. 10.6).

There is also an increase in PDC from right parietal to central channels in the Transcription condition after the creative writing workshop.

8.3.4 kSVM Classification Results

Automatic classification of EEG data into the tasks performed allows for the evaluation of feature relevance and discrimination, as well as their predictive power in classifying new data into the BO, BC, Tr, and CW classes. The creative writing

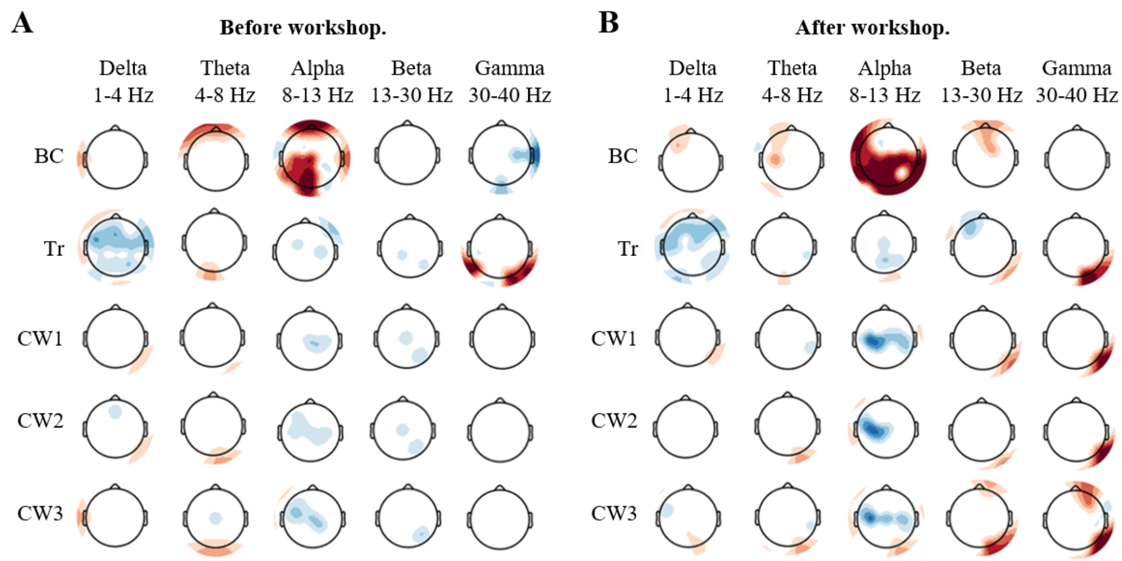

Figure 8.2: Band-power changes compared to BO. A) Before workshop. B) After workshop. Decreased delta power in Transcription; and decreased alpha power in central areas for all writing, stronger after workshop.

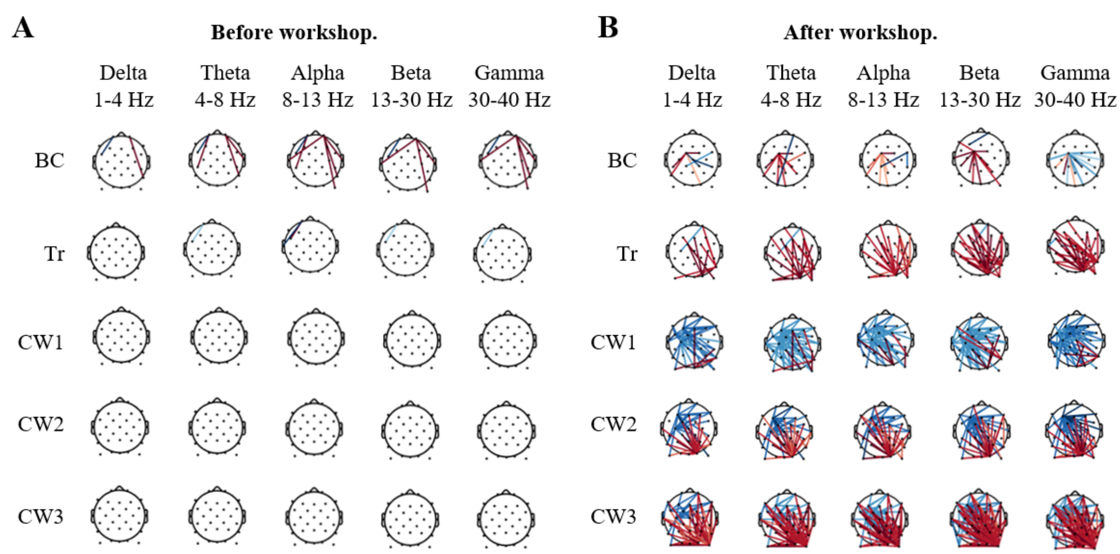

Figure 8.3: PDC changes compared to BO. A) Before workshop. B) After workshop. Increased PDC from right Parietal to left Central-Frontal areas after the workshop in all writing tasks; decreased PDC in the opposite direction.

tasks CW1, CW2, CW3, were collapsed into one single overall class: Creative Writing (CW)[3]. These tasks were classified using kSVM of polynomial degree 3. With temporal sub-sampling, the classification accuracy reached over 75% (chance level = 25%), providing evidence for the relevance of the neural features selected for task identification and characterization. This result, across students and creative writing texts (six per student), provide the first evidence that it is possible to classify tasks related to creative production in creative writing from EEG neural features alone: in unseen data taken from temporally different task incidences. The features driving the classification of these tasks are consistent throughout a creative writing production text based on pictures of locations as writing prompts.

The highest confusion in the temporal sub-sampling scheme is between Transcription and Creative Writing, as both are writing tasks. However, there is a clear distinction between them. From Fig. 8.3, the most apparent feature difference is on PDC. The PDC from frontal to central regions does not appear to be present in the Transcription task with the same strength as in the Creative Writing tasks.

This finding is consistent with the model of creative production proposed by Lui et al. [60], obtained from poetry improvisation analyzing neural data through fMRI. The propose that the dorsolateral pre-frontal cortex is deactivated during creative production, as compared to poetry memorization. We find an analogous component here, with PDC suppression from frontal to central electrodes being the feature that differentiates Transcription from Creative Writing.

[3] See Supplementary Materials 10.6 for classification results with CW1, CW2, and CW3 as separate classes. The largest confusion happens, predictably between these CW classes; reaching an overall mean accuracy of 59.3% for six classes: BO, BC, Tr, CW1, CW2, CW3.

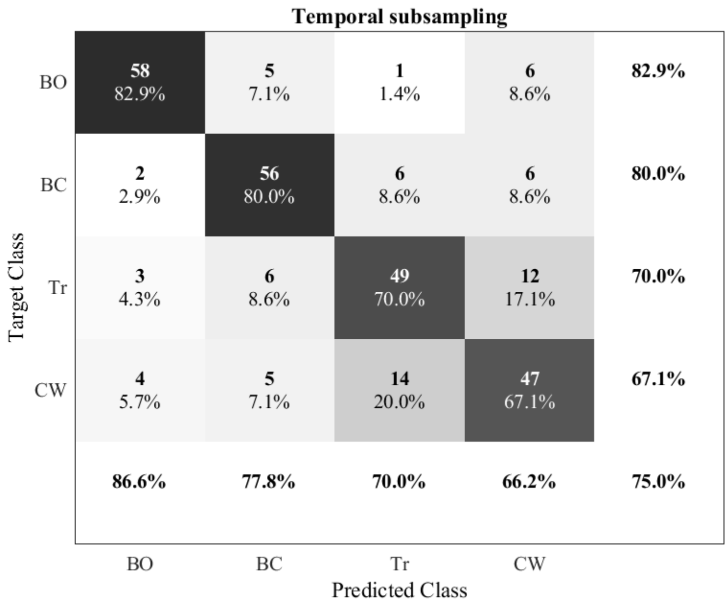

Figure 8.4: Confusion matrices for the kSVM classification results on temporal subsampling for the test set.

8.4 Discussion

By comparing the creative improvisational texts from before and after the creative writing workshop and having the students physically experience the locations in the prompts, we observed that there was a significant increase in PDC between right occipital and left central-frontal electrodes. This finding was observed both in Transcription and the Creative Writing conditions. Additionally, in the Transcription condition, we observed desynchronization in the frontal and central-frontal regions of the scalp in the delta band. The patterns observed were consistent across the students.

The changes in PDC comparing before and after the workshop were observed consistently in the Transcription task as well as in the Creative Writing tasks. Transcribing is not just a mechanical action [134]; rather, it is an intellectual endeavour:

"Even when we do something as seemingly 'uncreative' as retyping a few pages, we express ourselves in a variety of ways."[135] Students can identify poetic strategies used in the text they write by hand, the relation of the body and writing, and reflect on the dynamic qualities in the language they read.

The text analysis provided information on the strategies used by the students before and after the workshop. Less adjectives were used after the workshop, and more questions and reflections were observed in the creative texts after they had gone through the workshop. Again, the students seem to have taken language as a dynamic medium to reflect and transmit those reflections to the reader, both by reducing the number of descriptors used to modify words, but by evocating experiences through their texts.

Writing is the taking of decisions, a means for reflection and the sharing of such reflection; of taking language as a dynamic entity. Sharing texts, techniques, and experiences through a creative writing workshop created physiological changes in how the brain processes information in the students analyzed here. Notably, five out of six students' data showed increase information flow from from right parietal to central-frontal areas; and decreased information flow in the opposite direction (Fig. 10.7). Neurotechnology provided evidence for information flow changes in the students based on their experiences, matching their increased flexibility for experience evocation from the writing prompts.

We used power spectrum-related features and connectivity or information shared between electrodes for a classical machine learning analysis of neural feature extraction and classification. The approach proved successful in identifying features that relate specifically to creative writing production; namely: bi-directional PDC from right parietal and left central-frontal scalp areas.

8.5 Methods

Eight bilingual students participated in a creative writing workshop over the course of a semester. EEG data was collected in two sessions of creative writing and two sessions of discussion of their creative texts during the workshop. Fig. 8.5 shows the corresponding experimental timeline in the 14-week of the workshop. This experiment analyzes the effect of an intervention on training students in creative writing as an embodied, community practice, and relating changes seen after the workshop vs before the workshop in the neural features captured through EEG.

In this report, only the creative writing sessions before and after the workshop are analyzed: Week 1 and week 14 in the Fig. 8.5 diagram.

Brain activity was collected with 32 active-electrode EEG sampled at 1000 Hz (BrainAmpDC with actiCAP, Brain Products GmbH). Two electrodes were used for Horizontal Electro-Oculography tracking. The electrodes were placed in accordance with the 10–20 international system using FCz as reference and AFz as ground. A synchronized video camera was used to record the experiment.

The students wrote creative texts while wearing the EEG equipment in two time-constrained creative writing sessions. All writing was done by hand with pens and notebooks.

8.5.1 Pilot Data and EEG Metrics Proposed

In Chapter 7, we discussed pilot data that served the purpose of guiding us through best practices in the data collection process, and to formulate appropriate hypotheses. This pilot study aimed to identify EEG features related to the different stages of a creative writing task where subjects were able to move, explore their

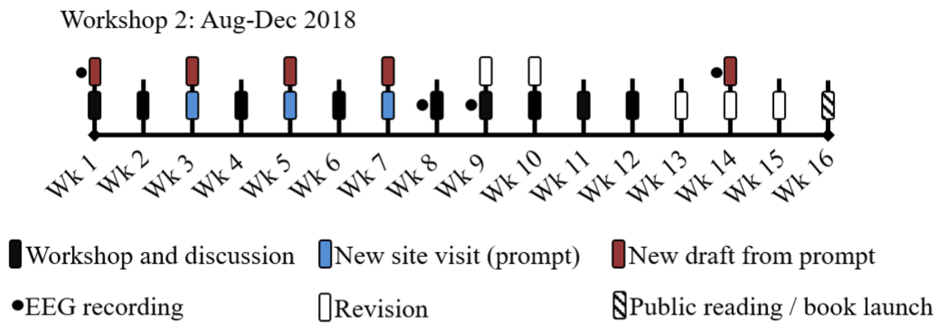

Figure 8.5: Creative Writing workshop 2. Timeline for the EEG recording sessions in the creative writing workshop: talleres de escrituras.

surroundings to inform their creative texts (Preparation Phase), and write at their own time (Generation Phase). The EEG features explored were partial directed coherence (PDC), sample entropy, and band-power in the delta, beta, alpha, beta, and gamma frequency bands.

The work reported in Chapter 7 was the first study investigating the neural features associated with creative writing using quantitative EEG metrics to compare different phases of the process.

The main findings in the pilot study were: 1) We found higher average Partial Directed Coherence during the Preparation phase from the right temporal electrodes towards left frontal electrodes; with opposite directionality in the Generation Phase. 2) No statistical differences in Sample Entropy or band power features across the four electrodes analyzed: TP09, TP10, AF07, AF08.

8.5.2 Creative Writing metrics proposed for text analysis

We analyzed the text created by the students before and after the creative writing workshop with two representative features: the number of adjectives used, and the number of questions posed by the students in their texts; both features were then normalized by the number of words in the corresponding text. The students used adjectives to describe nouns and spaces. The adjective brings particularity to nouns [136], a strategy likely used by the students to create an experience from the prompts. After physically experiencing the locations shown in the prompts, the students would be able to reflect upon that experience and transmit it to a reader. One of the students could not participate in the second creative writing session, after the workshop.

The text features proposed, number of adjectives, and number of concrete questions/reflections were abundant in our text samples, allowing for statistical analysis between the Before and After Workshop experimental comparison. There were 3.95±1.88 adjectives used per text, and 0.45±0.77 questions per text. Each student produced three texts Before and three texts After the workshop. One student did not attend the After-workshop recording session.

8.5.3 Experiment Design

During the time-constrained improvisational creative writing sessions, the students were given three writing prompts (2min each), preceded with periods of baseline with eyes open (1min), baseline eyes closed (1min), and a control condition where they transcribed a text (2min). See Fig. 8.6 for the list of tasks and a pictures of the experimental setup with students wearing the EEG caps.

The creative writing prompts consisted of pictures of the Second Ward in Houston, a historically multicultural neighborhood adjacent to the University of Houston. Through the course of the semester, the students experienced the pictures locations, interacted with the community there, collected samples, and created creative texts based on their experience. Supplementary Materials Fig. 10.5 shows the pictures used as prompts, and pictures of the students visiting the locations together. The

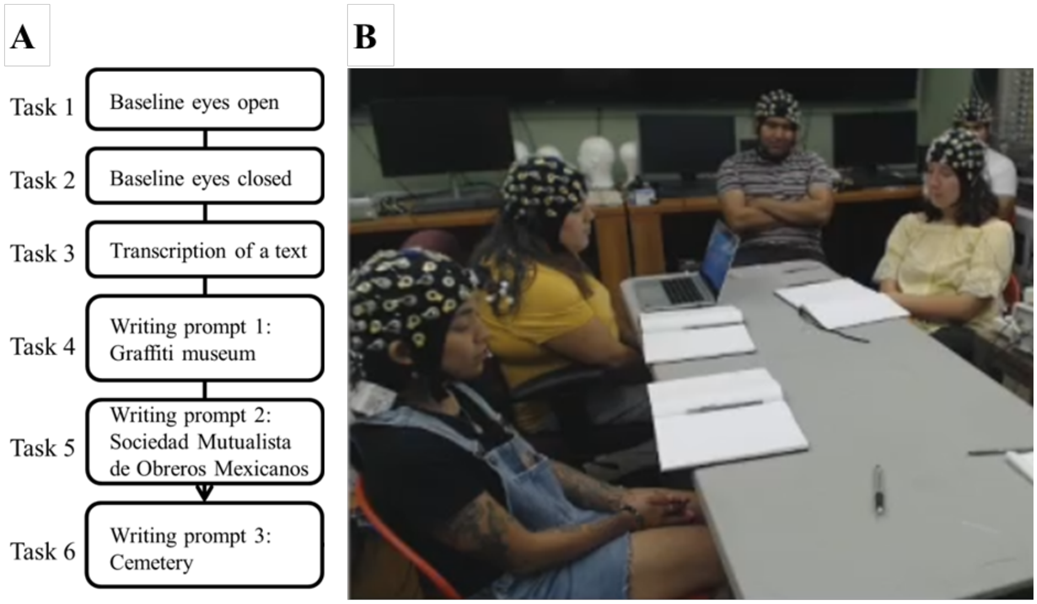

Figure 8.6: Experimental setup for the creative writing tasks before and after the workshop. A) Experimental tasks. B) Picture of the students, EEG recording system, and notebooks for the tasks.

creative text drafts were discussed between them, guided by the instructor remarks.

At the end of the semester, the students repeated the creative writing experimental session, now having had experienced the locations and worked with them through the course. There are two creative writing sessions analyzed: The list of tasks in Fig. 8.6A before the workshop in week 1, and the same list of tasks and prompts after the workshop in week 14.

8.5.4 EEG Data Analysis

Data driven neuroscience studies have found great success in applying supervised and unsupervised machine learning techniques to find relationships between the data collected and a behavioral response observed. Classical machine learning requires the researcher to identify and select features of the data to analyze. In EEG, these features usually take the form of power in specific frequency bands or commonly used frequency bands: e.g., delta 1-4 Hz, theta 4-8 Hz, alpha 8-12 Hz, beta 12-30 Hz, gamma 30-50 Hz. Time domain features involving temporal and spatial relationships between the data have been used successfully to decode movement intent in mobile settings ([19, 117, 17, 18, 33]). Quantitative neuroscience based on EEG has developed importantly through a combination of spectral, statistical, and spatial features, researchers are able to build a set of descriptors to feed into machine learning algorithms [23].

8.5.5 EEG Data Pre-Processing

The unconstrained nature of the experiment makes the EEG data susceptible to artifacts including motion-related artifacts. Electrode impedance was obtained before and after the experiment. Electrodes with impedance values above $60k\Omega$ were removed. The EEG data was resampled from 1000 Hz to 250 Hz. The EEG data was high-pass filtered at 1 Hz using a 4th order zero-phase Butterworth filter. A notch filter will be applied at 60 Hz to remove powerline noise. The H^{∞} ($gamma = 1.15$, $q_0 = 1x10^{-10}$) filter [119] was used to remove eye-movement contamination. The horizontal EOG electrodes were low-pass filtered at 10 Hz before running the H^{∞} filter. We followed the PREP pipeline [111] for standardized robust referencing: notch filter at 60 Hz, robust re-referencing using common average reference and excluding high-impedance channels. We used Artifact Subspace Reconstruction [120] to remove bursts of abnormal activity due to other types of artifacts.

8.5.6 Classical Machine Learning

8.5.7 Feature Selection

The most relevant features across subjects were selected using a mutual information implementation of the mRMR [42] algorithm. In mRMR, a feature score is sequentially calculated by computing the mutual information between each feature and the target/class vector; and subtracting the redundancy term: average mutual information between each remaining feature and the previous selected features.

8.5.8 Classification

The classical machine learning classifier used for the EEG and motion data was the kernel support vector machine (kSVM), using the polynomial kernel of degree 3. The value of the and box-constraint was set to 1 in all cases.

Classical machine learning techniques involve a combination of hand-crafted features, based on previous neuroscience, to approach the problem. These features are then set as input for a classifier. We used band power features for each channel and PDC between all channel pair combinations as features, in 4 second windows with 50% overlap. The features obtained in each of these data windows constitutes constitute a data sample. The data samples from all subjects were analyzed together. We selected randomly, with repetition, $N_s = 300$ samples per class, to achieve class balance.

The training, validation, and test sets were taken in temporal subsampling. The data from the first temporal 80% of the experiment was selected for the training and validation sets, while the last temporal 20% was selected for the test set. From those samples, ($N_s = 300$) samples were selected to achieve class balance, divided into ($N_s = 230$) samples for the training and validation sets, and ($N_s = 70$) for the test set.

8.6 Class labels

The task labels were directly taken from the tasks proposed in the experiment design, Fig. 8.6A. The class labels were: Baseline Eyes Open (BO), Baseline Eyes Closed (BC), Transcription (Tr), Creative Writing Prompt 1 (CW1), Creative Writing Prompt 2 (CW2), Creative Writing Prompt 3 (CW3). The three creative writing conditions were concatenated into one single class: Creative Writing (CW).

8.7 Acknowledgements

The authors thank the members of the Laboratory for Noninvasive Brain-Machine Interface System for assistance during data collection. We also thank Majo Delgadillo for assisting in conducting the workshop and experiment sessions, and leading the site visits.

This research was funded in part by NSF award #BCS1533691, NSF IUCRC BRAIN Award CNS1650536, a Seed Grant from the Cullen College of Engineering at the University of Houston, and the SeFAC grant from the Center for Advanced Computing and Data Science (CACDS) at the University of Houston.

8.8 Author Contributions Statement

JGCG collected the data, performed the data analysis, and wrote the manuscript. JGCG and CRG planned the experiment. CRG planned and conducted the workshop. JLC-V and CRG conceived the research and edited the manuscript. All authors reviewed the manuscript.

Chapter 9

Conclusion

This dissertation provides two major conclusions based on two experiments and one pilot study, analyzing the neural features associated to the human creative process in real world settings using MoBI.

First, we found connectivity patterns connecting right parietal with left central-frontal areas of the scalp during creative execution, which are enhanced with training and physical experience of the creative process; these patterns are found in higher proportion in creative writing tasks. These connectivity patterns, together with band power EEG features, provide relevant information for classification of creative tasks based solely on EEG data: over 53.5% in temporally different test data (from the training/ validation sets) for five classes in the visual arts experiment, and over 79.3% in the creative writing experiment with four classes.

Second, we can implement automatic feature extraction methods based on CNNs with predictive capabilities, and these features clearly resemble those found by classical feature extraction in the field. Automatic feature extraction provides a venue for finding previously undisclosed features that drive the human creative process, benefiting from increasing and more diverse training data, in terms of creative production.

Additionally, we demonstrate the possibility to deploy MoBI technology to study the human creative process in freely-moving participants; including integrating real-world courses with the technology to enhance both the students' inter-disciplinary experience, and for neuroscience-relevant data acquisition that shed light into the neural dynamics involved in real-world creative production. The experiments yielded quality data while at the same time providing opportunities for scientific outreach (Chapter 6), and its implementation in creative writing production, and reflection, and as an integrated part of a course (Chapter 7, 8).

9.1 Connectivity Patterns Between Right Parietal and Left Central-Frontal Locations are Found in Creative Ideation and Production

In the visual arts experiment (Chapter 6), high connectivity patterns emerged in execution tasks: mark making, and writing. The patterns during the writing actions were most prominent, even if 'writing' was placing letters into words and sentences on the canvas.

In our pilot data experiment (Chapter 7) to analyze the Preparation and Generation stages of the writing process, the connectivity patterns that primarily emerged across subjects connected right parietal with left frontal scalp areas. The preparation phase contained stronger connection with frontal to parietal directionality; while in the text generation phase, the strongest connections occurred from parietal to frontal areas.

In the creative writing experiment (Chapter 8), comparing creative improvisational texts, from before and after a creative writing workshop, the same connectivity patterns were observed to be the most discriminant feature between the two conditions: before and after the experiment. As in the previous experiments, these patters connected the right parietal with central-frontal regions of the scalp electrodes consistently across participants. The patterns occurred after the students went through the creative writing workshop, appearing in text transcription and creative writing production.

Our results relate to previous findings in fMRI studies analyzing the different stages of the creative process. Shah et al. [126] found that the ventrolateral prefrontal cortex was activated during the Preparation phase, while central-parietal areas were involved in the Generation phase. “Brainstorming” engaged cognitive, linguistic, and creative functions represented in a parieto-frontal-temporal network. “Creative writing” activated motor, visual, a cognitive and linguistic areas over central and parietal networks [126]. In [60], the authors found that the medial prefrontal cortex was active during the generation and revision phases.

Overall, these findings suggest that ideation, exploration, and observation in creative execution tasks can be characterized by a state of long-range cortico-cortical communication between multisensory integration brain areas (parietal and temporal regions) and high-order execution and planning areas of the brain (frontal regions).

9.2 Automatic Feature Extraction Algorithms Find Appropriate Features to Characterize the Human Creative Process

Our data-driven approach for automatic feature extraction based on CNNs shows promise to uncover neural patterns relevant for creative task identification.

We tested the relevance of the features proposed and accurately classified creative actions based solely on EEG features, using classical machine learning feature extraction and classification. The automatic feature selection method was able to classify EEG data into creative tasks as well. Crucially, in automatic feature extraction methods, it is important to visualize the features being learned by the network, and corroborate their relevance based on known neuroscience [44].

The accuracies obtained by the CNN approach did not significantly improve on the accuracies obtained in the classical machine learning approach. However, it does show potential for applicability as the work presented here allows us to think of the possibility of moving towards big-data real-world neuroscience [22, 112, 113, 54]. The possibility for large scale, high quality, and labeled EEG data with the implementation of context-aware MoBI in a variety of tasks makes the deep learning approach appealing for automatic feature identification and classification.

9.3 Broader Impacts

This research brings together scientists, artists, students, and the Houston community in a robust and truly interdisciplinary collaboration. The collaboration ranges from multimodal MoBI data acquisition, science, technology, engineering, art, and mathematics (STEAM) outreach activities, neuroscience-informed artistic production, community engagement initiatives, and the potential application of the new knowledge generated through the research in ergonomic intervention through design and educational resources [137, 138, 139]. This research has served as a platform for international, interdisciplinary collaboration dedicated to characterizing the human creative process through neuroscience [110], but it has also developed a strong foundation through which we can use the results of this work to train, promote collaboration, and motivate future generations of scientists, artists, teachers, and community leaders [140].

The research on the neural basis of creative writing, through skill development to draft production and publication, has been a community engagement initiative from its inception. First, we explore the idea of writing as an embodied experience, in which writing is generated in the presence of others, through the interaction with others. This experiment consisted of two courses in creative writing at the University of Houston, in a partnership with the department of Hispanic Studies and Electrical and Computer Engineering. In the first course, students were equipped with synchronized wearable cameras and mobile EEG as they walked through the city of Houston and wrote about their experiences. In the second course, the students wrote the Houston Second Ward. Bilingual students interacted with the community in the Second Ward, a historically Mexican neighborhood adjacent to the University of Houston. Such courses are critically lacking in the university experience, in which the truly robust transdisciplinarity directly engage with the community through artistic reflection and creation

The students used the neuroscience data to inform their writing and their bodily experiences as they reflected on their visits to specific locations in the Second Ward. The outcome of the class was a book published under Canal Press, “Bienvenido, you have been transported” [141].

The research, discussion, and the evolving language used to bridge communication between artists and scientists has produced a book, "Mobile Brain–Body Imaging and the Neuroscience of Art, Innovation and Creativity", edited by Jose L. Contreras-Vidal, Dario Robleto, Jesus G. Cruz-Garza, José M. Azorín, Chang S. Nam [104]. Additionally, the research has produced two book chapters [97, 1] in the 2019 book “Brain Art” [142]. Both of these books are intended for broad audiences in the arts, engineering, science, and in the arts. They provide state-of-the art tangible BCI performance for artistic creation. Further, they contextualize current progress in the field by providing a theoretical framework for future inquiry, and a roadmap for convergent research, for harnessing emerging machine learning techniques for feature visualization, and to examining individuality and variation [143] in the creative process. In [110], we discuss the value of developing a conversation to properly examine the provocative outcomes produced by the transdisciplinary inquiry of the neuroscience of the human creative process.

Chapter 10

Supplementary Materials

This section contains supplementary materials for the dissertation.

Previously Proposed Phases of Creativity	**Exquisite Corpse Classes**	Subclasses for Broad Strokes and Short Strokes
Pre-planning (Kozbelt 2008)	1. Baseline eyes closed 2. Baseline eyes open	
Exploring ideas, **Planning** (Finke, Ward, and Smith 1992)	3. Planning/Observing 4. Cutting	
Generation, Elaboration, **Execution** (Liu et al. 2015; Simonton 1984; Kozbelt 2008).	5. Broad strokes 6. Short strokes 7. Placing down on art piece	a. Outlining b. Tracing c. Coloring d. Spreading e. Drawing f. Writing
Revision (Liu et al. 2015)	8. Correction	

Table 10.1: Phases in the human creative processes proposed in the neuroscience literature.

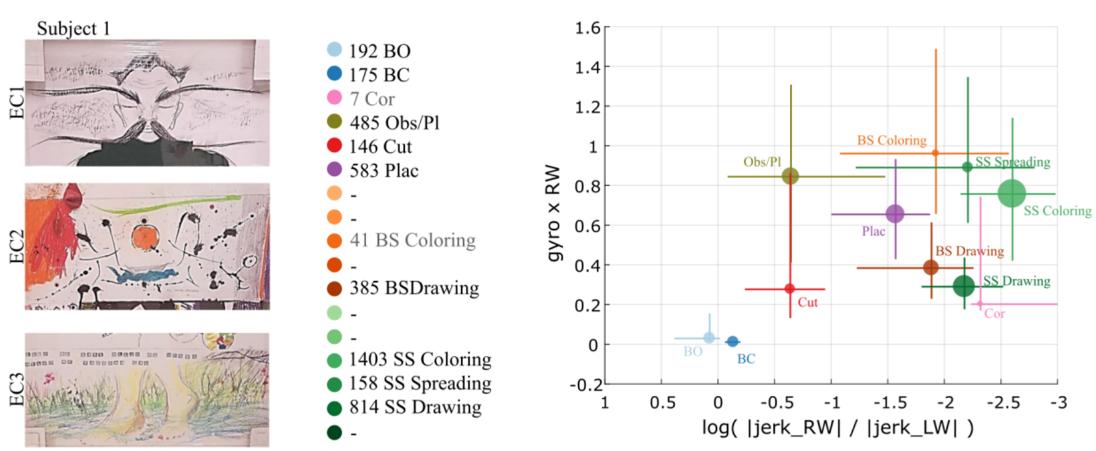

Figure 10.1: Kinematic characterization the classes analyzed in Artist 1. The numbers in the middle panel represent the number of examples from each class.

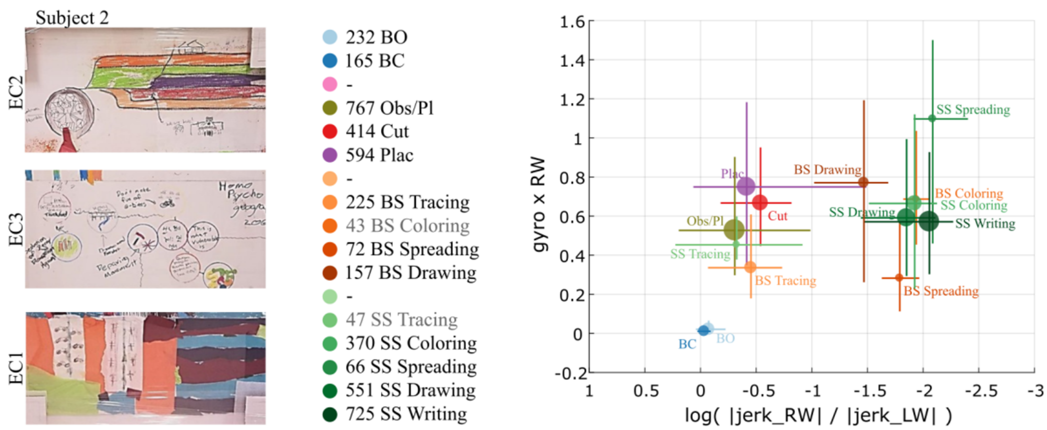

Figure 10.2: Kinematic characterization the classes analyzed in Artist 2. The numbers in the middle panel represent the number of examples from each class.

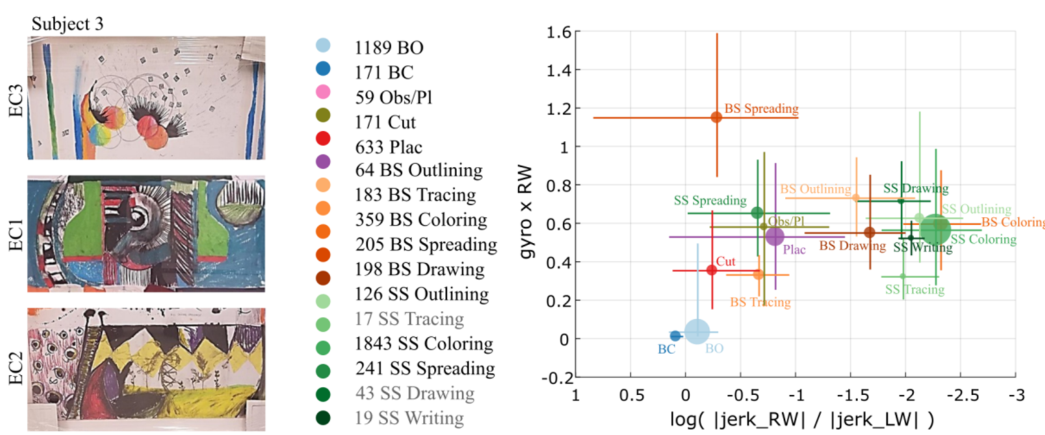

Figure 10.3: Kinematic characterization the classes analyzed in Artist 3. The numbers in the middle panel represent the number of examples from each class.

Table 10.2: mRMR results table. The feature rank indicates that the features shared the most mutual information with the class vector and the average least mutual information with previously selected features.

Rank	Type	Frequency Band	Electrodes
1	Band-Power	Alpha	F4
2	PDC	Beta	FC5 to P8
3	Band-Power	Gamma	FC4
4	Band-Power	Delta	Oz
5	PDC	Beta	O2 to CP1
6	Band-Power	Beta	CPz
7	Band-Power	Theta	TP8
8	Band-Power	Beta	FC4
9	Band-Power	Delta	PO7
10	Band-Power	Alpha	Pz
11	Band-Power	Gamma	P1
12	PDC	Alpha	O2 to FC1
13	Band-Power	Theta	AF4
14	Band-Power	Gamma	P3
15	Band-Power	Beta	C6
16	PDC	Gamma	O2 to FC5
17	Band-Power	Theta	FC2
18	Band-Power	Theta	P6
19	PDC	Delta	O2 to CP5
20	Band-Power	Alpha	FC4
21	PDC	Beta	FC1 to P8
22	Band-Power	Theta	PO8
23	Band-Power	Gamma	FC3
24	PDC	Gamma	O2 to CP5
25	Band-Power	Delta	FC1
26	PDC	Beta	FC5 to Oz
27	Band-Power	Theta	Oz
28	PDC	Alpha	O2 to CP1
29	Band-Power	Gamma	TP8
30	PDC	Delta	FC5 to Oz
31	Band-Power	Beta	P3
32	Band-Power	Gamma	C6
33	Band-Power	Delta	O1
34	PDC	Beta	C3 to P8
35	PDC	Beta	O2 to FC5
36	Band-Power	Gamma	P2
37	Band-Power	Theta	FC3
38	PDC	Alpha	FC5 to O2
39	Band-Power	Delta	F4
40	PDC	Delta	O2 to CP1
41	PDC	Alpha	CP1 to O2
42	Band-Power	Gamma	PO8
43	PDC	Gamma	FC5 to Oz
44	PDC	Gamma	O2 to CP1
45	Band-Power	Alpha	FC1
46	Band-Power	Gamma	Cz
47	Band-Power	Theta	F5
48	PDC	Beta	P8 to FC1
49	PDC	Alpha	O2 to T7
50	Band-Power	Theta	POz

Table 10.3: Detail of neuroscience literature where the task evaluated involved creative writing as an experimental task. Part 1: Experiments that compare resting state EEG with creative scores from a test.

Study	Measurement	Task	Experimental design	Findings
Martindale and Hasenfus 1978	EEG	Writing: Creative inspiration vs creative production	Measure EEG as subjects think what to write and while they write. Number of subjects = 12	Highly creative individuals exhibited higher alpha indices during a creative inspiration (preparation) than creative elaboration (generation); which was not found in less creative subjects.
Jausovic 2000.	EEG	Dialectic problem: Read a text, and think about writing an essay about it.	Measure EEG data as the subjects think about writing an essay. Number of subjects = 48.	Higher alpha power across the scalp in individuals who performed better at creative problem solving. Creative individuals showed higher coherence across the scalp, in the alpha band.
Jausovic & Jausovic 2000.	EEG	Dialectic problem: Read a text, and think about writing an essay about it.	Measure EEG at rest. Correlate EEG features with creativity scores. Number of subjects = 115	Weak correlations between power, frequency, and approx. entropy with creativity score. General low coherence Right hemisphere high coherence during resting state for highly creative individuals.
Takeuchi et al. 2012.	fMRI	Divergent Thinking test	Measure rFC. Number of subjects = 159.	Positive and significant correlation in rFC between the mPFC and PCC and creativity score. No correlation in right or left DLPFC with any brain area and creativity score.
Wei et al. 2014.	fMRI	Divergent Thinking test	1) Measure rFC. Number of subjects = 269. 2) Subset of subjects perform the AUT. Number of subjects = 34. 3) Measure rFC from after AUT. Number of subjects = 34.	Increased rFC between mPFC and the mTG in individuals with higher creativity score. The rFC can be further increased by cognitive stimulation (AUT).
Lotze et al. 2014.	fMRI	Verbal Creativity Index (Test)	Measure rFC. Experts and non-experts continue a literary text. Number of subjects = 43 (23 experts).	Decreased rFC for experts was found between interhemispheric areas 44. Increased rFC for experts was observed between right hemispheric caudate and IPS. Negative correlation between verbal creative index and rFC between left area 44 and left temporal pole.

Table 10.4: Detail of neuroscience literature where the task evaluated involved creative writing as an experimental task. Part 2: Experiments that compare stages of the creative process. None with EEG, nor in a real-world setting until this report.

Study	Measurement	Task	Experimental design	Findings
Howard-Jones et al., 2004.	fMRI	Semantic divergence: Create a story from a set of words.	Monitor fMRI activations as participants think about the stories. Number of subjects = 8.	Comparing creative vs noncreative story generation: Activations observed within bilateral medial frontal gyri (BAs 9 and 10) and the left anterior cingulate (BA 32).
Shah et al. 2013.	fMRI	Verbal creativity test Rating of creative product	"Brainstorming" and "creative writing". Number of subjects = 28.	"Brainstorming" engaged cognitive, linguistic, and creative brain functions mainly represented in a parieto-frontal-temporal network. "Creative writing" activated motor and visual brain areas for handwriting and additionally, cognitive and linguistic areas. Correlation of "creative writing" minus "copying" with the creativity index revealed activation in the left inferior frontal gyrus (BA 45) and the left temporal pole (BA 38).
Erhard et al. 2014.	fMRI	Verbal creativity test Rating of creative product	"Brainstorming" and "creative writing". Experts and non-experts continue a literary text. Number of subjects = 48.	Experts showed increased activation in prefrontal (mPFC and DLPFC) and basal ganglia (caudate) areas. High verbal creativity increases activation in the right cuneus.
Liu et al. 2015.	fMRI	Poetry composition: Generation and Revision.	Poetry composition. "Generation" and "Revision". 1) Memorized poems. 2) Generation of new poems. 3) Revision of poems. 4) Random typing. 5) Non-memorized facts. 6) Memorized facts. Number of subjects = 27 (14 experts / 13 non-experts).	mPFC active during both phases. Responses in DLPFC and IPS were attenuated during generation and activated during revision. Experts showed significantly stronger deactivation of DLPFC/IPS during generation. Activation of IFG, left mTG, and STG in the generation phase.
Cruz-Garza et al. 2019. **This report.**	EEG 4-channels: AF09, AF10, TP09, TP10.	Composition of creative texts based on walking/ experiencing different city locations.	Text "Preparation" and "Generation" phases. Up to five writing exercises. Number of subjects = 7 non-experts.	Higher average PDC during the Preparation phase. High coherence was observed in connections originating in the temporal electrodes towards frontal and temporal electrodes. Higher values of SampEn during Generation Phase. Higher band-power in the Alpha, Beta and Gamma bands during the Generation phase.

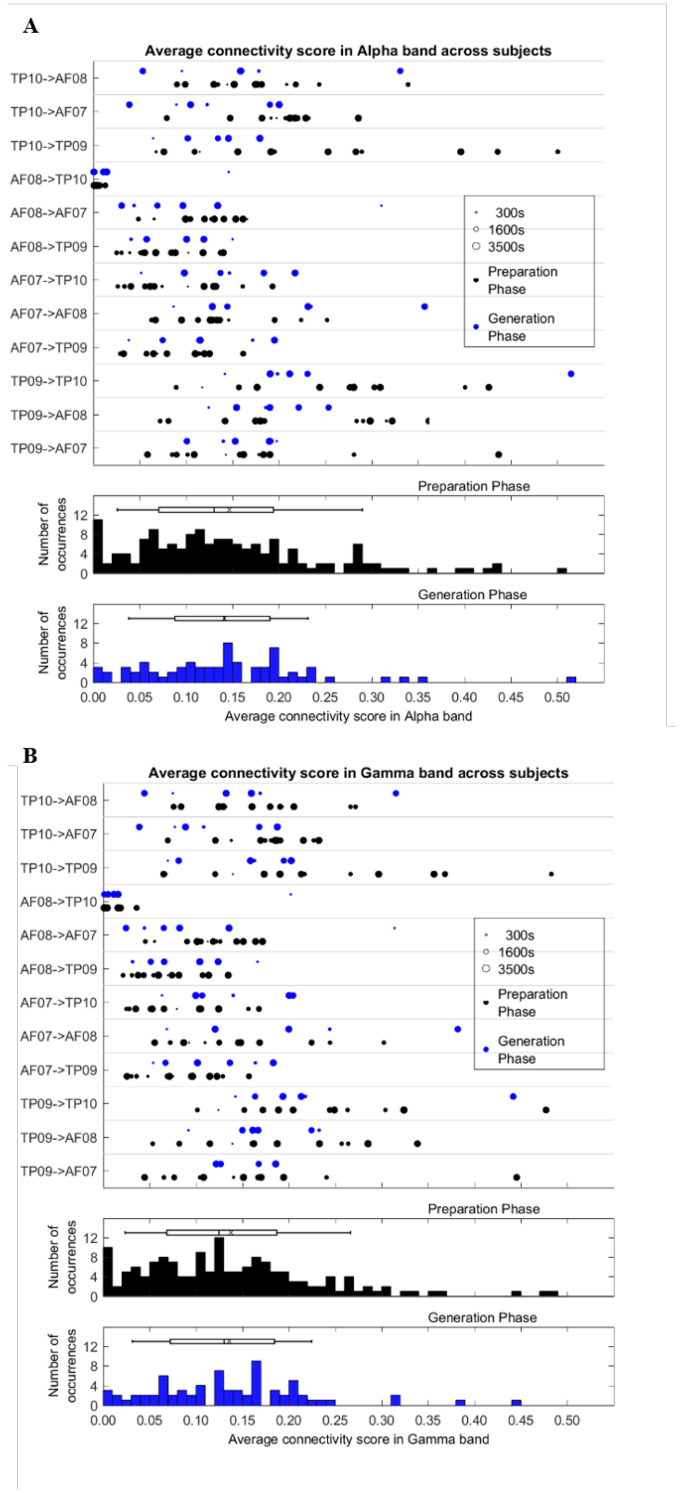

Figure 10.4: PDC distributions in A) alpha band, B) gamma band. Average PDC for each directed connection pair. EEG recording sessions marked as circles. A histogram of the distributions is shown in the bottom panels.

Figure 10.5: Detail of creative writing prompts. A) Pictures shown during the creative writing EEG recording sessions. B) During the creative writing workshop, the students experienced the locations in community.

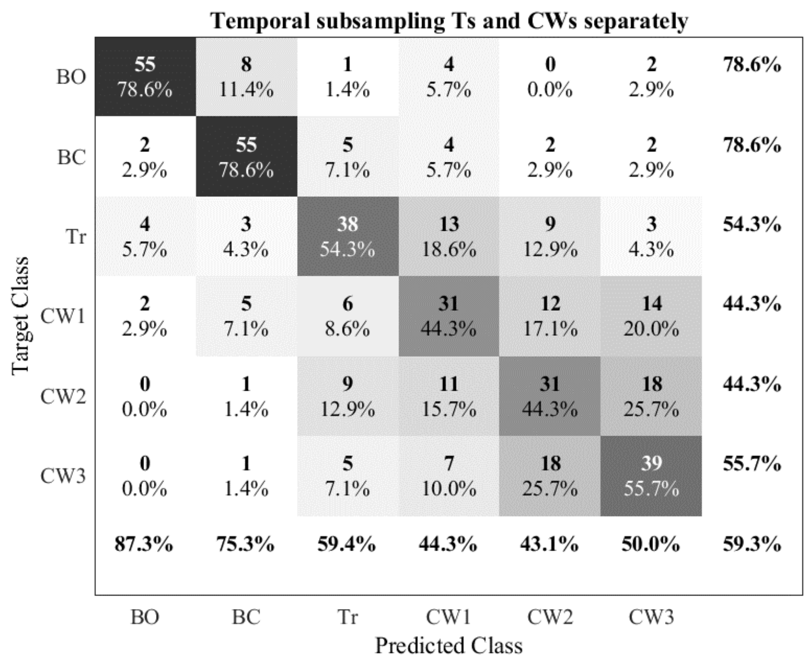

Figure 10.6: Confusion matrix in the test set for the creative writing tasks: the three prompts are classified separately: CW1-3. The EEG feature distributions within those tasks are comparable: high confusion among them.

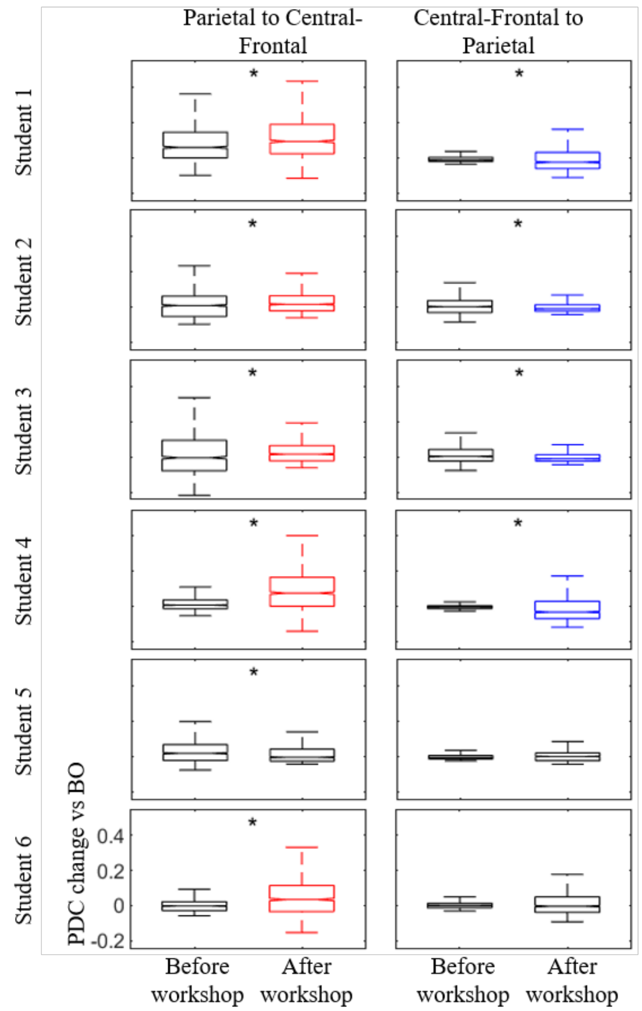

Figure 10.7: PDC distributions before and after the 16-week creative writing workshop. There are consistent and significant changes in the distributions in five out of six subjects. Kruskal-Wallis test at 5% significance level.

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