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Potentiality of Entropy for Semantic Concept Differentiation in EEG Signals in Alpha and Beta Waves

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Abstract

Semantic feature extraction is a novel field in neurotechnology research and is quickly growing in interest for its many applications, ranging from education to rehabilitation to BCIs. With few studies existing on the subject, a wide range of possibilities open for exploration. While most of the current related research landscape explored the implementation of time-domain and frequency-domain features, this study proposes an approach based on entropy measures. exploring their potentiality for differentiation between concepts. This study focused on the analysis of entropy measures computed on EEG signals as, while offering less spatial resolution compared to other brain signal acquisition technologies, it best suits real-life application thanks to its portability, low cost, and current developments for this purpose. Entropy was chosen for this purpose due to its fundaments in the information theory, potentially bypassing other features limitations. For this study EEG signals have been divided based on the concept used for stimulation through different methods and paradigms (pictorial, orthographic and auditory comprehension, repeated for perception and imagination tasks) to limit the influence on the results of the modality-related processing pathways in brain activity and bring focus to the concepts. Different entropy measures, Shannon entropy, spectral entropy, sample entropy, permutation entropy, and multiscale entropy, have been calculated from the EEG signals in two bandwidths, alpha and beta, and the results across the electrodes were assessed through visual and statistical analysis. The visual analysis was performed with the help of 2D plots of each electrode's entropy value on the scalp and with histograms. The statistical analysis consisted in an Analysis of Variance (ANOVA) including all three concepts (guitar, flower, and penguin) and t-tests performed on all pairs of concepts. The results suggest that alpha waves have better results compared to beta. Additionally, a tendency suggesting Shannon, sample and multiscale entropies could better perform in distinguishing concepts was observed. Sample entropy showed the best results. Multiscale entropy results could suggest how certain time windows at different time scales can hold more information than others, also highlighting how these time windows can vary across subjects and trials. Some interesting trends were also observed in multiscale entropy in alpha waves. Despite its limitations, this study can serve as a first step towards the creation of new methods for performing semantic feature extraction using algorithms specifically tailored on the different entropy features.

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1.1 Introduction to Brain Signals

1.1.1 Overview of Brain Signals

The brain is a highly complex network of neurons, each capable of sending and receiving messages that influence everything we experience, from basic body functions to complex reasoning and thoughts. Brain signals are generated from the communication between neurons in the brain, which happens via electrical and chemical signals. Neurons, fundamental elements of the brain, are cells with a unique structure. The structure, represented in Fig. 1, is composed of the soma, the cell's main body holding the nucleus and the cytoplasm; the dendrites, branch-like structures that extend from the soma and that receive signals from other cells; and the axon, a long projection that transmits electric impulses to other cells from its terminations. These terminations create a structure with the dendrites of other neurons called a synapse. Electrical signals are generated by the propagation of the action potentials along neurons, while chemical signals happen in the synapses through the release of neurotransmitters (Lovinger, 2008). Brain signals are thus generated from the electrical activity and communication processes that occur within the brain, whether in an active state or at rest (Smith et al., 2009). In conclusion, brain signals are time-series representations of brain activity that contain biometric information crucial for understanding brain activity and mapping neural pathways (Schirrmeister et al., 2017).

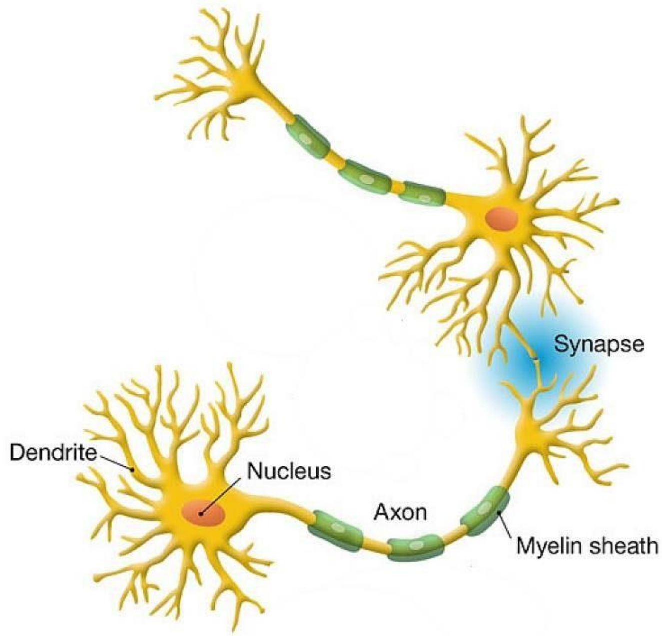

Figure 1: Representation of neuronal structure

1.1.2 Types of brain signals

Brain signals can be categorized into different types based on their characteristics and applications. An Electroencephalogram (EEG) records the electrical activity of the brain. On the other hand, a magnetoencephalogram (MEG) records the magnetic fields generated by brain activity. Functional magnetic resonance imaging (fMRI) follows a different approach, recording brain activity and measuring changes in blood flow and oxygen levels (Glover, 2011; Lopes da Silva, 2013).

1.1.3 Brief history of brain signal research

After Luigi Galvani first observed the role of electricity in nerve activity in 1792, Emil du Bois-Raymond furthered the understanding of electrical properties in neurons by giving birth to electrophysiology, the study of electrical activity in living cells. In 1929, the psychiatrist Hans Berger created a breakthrough in the field by developing the EEG, which provided the first glimpse into ongoing brain processes. The mechanism of neuronal communication was later unraveled by Hodgkin and Huxley, among others (Catterall et al., 2012). In the modern era, brain imaging techniques like fMRIs and PET scans allowed researchers to observe brain activity, identify neural pathways, and map the brain (Biswal et al., 2010).

1.1.4 Complexity of Brain Signals

The complexity of brain signals is a well-known topic in neuroscience research. Brain signals present intricate nonlinear dynamics, prompting a surge in complexity analyses (Sun et al., 2020). Studies have shown that brain signal's complexity increases with development, reflecting more specialized and differentiated brain regions capable of a broader range of neural dynamics (Vakorin et al., 2011) suggesting more efficient neural communication and increased information processing capabilities (Thiele et al., 2023). Brain signals' complexity is crucial for studying brain development, cognitive outcomes, neurological disorders, and age-related changes in brain activity (Grundy et al., 2017; Sortica da Costa et al., 2017).

1.1.5 Intricacy of brain functions and neural activities

The complexity of brain functions and neural activities is a multifaceted area of study that delves into the complex dynamics of the brain's operational mechanisms. Measures such as Neural Complexity aim to capture the interplay between functionally segregated and integrated neuronal groups, providing insights into different levels of consciousness (Agarwal et al., 2019) and encompass the fundamental aspects of brain organization, resolving conflicting views on local versus global brain functions (Tononi et al., 1994). Correlated spontaneous activity among neurons suggests a universal principle underlying the self-organization of complex neural circuits, although the precise mechanisms and functional roles remain unknown (Masumura et al., n.d.). The synchronization of neurons within the cerebral cortex forms the basis for various neurobiological processes closely linked to brain function and diseases (Uhlhaas et al., 2009).

1.1.6 Non-linear and Dynamic Nature of Brain Signals

Brain signals' dynamic and non-linear nature is a captivating area of research that delves into the intricate and complex dynamics of neural activities. Brain signals exhibit scale-free properties with complex spatiotemporal structures modulated by task performance (He, 2011). The variability of brain signals, stemming from their non-linear nature, is characterized by dynamical non-stationarity, reflecting the dynamic non-linear properties of the brain (Vakorin et al., 2013). Non-linear bistable dynamical models have been utilized to analyze EEG signals, underscoring the significance of non-linear dynamics in signal discrimination (Ying et al., 2015). The study of intraregional temporal features in fMRI data reveals the broadened dynamic range of brain signals when synchronized with other brain regions (B. Wang et al., 2023). The spectral properties of the temporal evolution of brain network structure unveil the dynamic nature of brain networks and their spectral fluctuation properties (Keilholz et al., 2020).

1.1.7 Challenges in Interpreting Brain Signals

The interpretation of brain signals can be highly challenging due to the complexity and dynamic nature of neural activity, making it difficult to extract meaningful information and draw accurate conclusions. Understanding the interplay between neural dynamics, hemodynamics, and information processing is crucial for effectively interpreting brain signals (Moore & Cao, 2008). Challenges in interpreting brain signals are evident in user control with

Brain-Computer Interfaces (BCIs) due to noisy and erratic low-dimensional motion commands resulting from the difficulty in decoding neural activity (Muelling et al., 2015). The surrounding environment also impacts the brain, adding more complexity to extracting information from brain signals. This is crucial when deciding the experiment's setup and, even in real-life scenarios where subjects simultaneously deal with multiple stimuli.

1.2 Importance of Exploring and Analyzing Brain Signals

1.2.1 Scientific and Medical Significance

Exploring and analyzing brain signals is of paramount scientific and medical significance due to the wealth of information they carry about brain function and health. Brain signals, such as EEG and MEG, provide insights into cognitive processes and neurological disorders like epilepsy, Alzheimer's, and Parkinson's disease, and even aid in understanding brain complexity with applications in brain-computer interfaces and machine learning. Techniques like signal processing, feature extraction, connectivity analysis, and classification models play crucial roles in interpreting brain signals accurately. Brain signal analysis enhances our understanding of brain dynamics and opens avenues for medical diagnosis, treatment, and cognitive research.

1.2.2 Understanding brain function and cognitive processes

Studies have shown that brain networks significantly support complex cognitive tasks (Downar et al., 2016). These networks, including default-mode networks and others, are involved in various functions like memory, executive functioning, and sensory processing (Damoiseaux et al., 2006). Brain signal analysis can also reveal the neural circuits responsible for decision-making, risk evaluation, and intention to act (Rocha et al., 2013). Investigating brain signals is essential for unraveling the intricacies of brain function and cognitive processes.

1.2.3 Applications in diagnosing neurological disorders

Analyzing brain signals is crucial in diagnosing neurological disorders. Techniques such as EEG signal analysis, machine learning, and connectivity analysis have been utilized to identify conditions like epilepsy, Alzheimer's, Parkinson's disease, and depression (Alonso et al., 2011; Alturki et al., 2020; Guerrero et al., 2021). Research has demonstrated that EEG data can offer valuable insights into brain disorders, facilitating early diagnosis and treatment (Fred et al., 2022). Moreover, applicating advanced technologies like neural activity recordings and high-density electrode arrays presents promising opportunities to enhance the accuracy and efficiency of diagnosing neurological conditions (Du et al., 2019). By utilizing these analytical methods and state-of-the-art technologies, healthcare professionals can improve their ability to identify and manage various neurological disorders effectively.

1.2.4 Enhancements in brain-machine interfaces

Brain-machine interface enhancement through brain signal analysis has revolutionized neuroprosthetic applications, aiding patients with brain injuries and neurodegenerative diseases (Andersen et al., 2014). By utilizing closed-loop brain-machine interfaces, individuals can control external devices through neural signals, enabling movement even for paralyzed individuals (Serino et al., 2022). Also, the integration of spiking neural networks and machine learning techniques has shown promise in enhancing brain-machine interface technology due to their low power cost and biological similarity (Taeckens et al., 2023; Waytowich et al., 2016).

1.2.5 Technological and Research Impacts

Brain signals analysis intensely promoted technological and research advancements. The development of implantable neural probes and advanced electrode materials has significantly improved the accuracy and efficiency of brain-machine interfaces (Choi et al., 2018; Wu et al., 2021). Initiatives like the BRAIN Initiative aim to advance innovative neurotechnologies to understand brain function dynamically, integrating neuronal and circuit activity over time and space (Bargmann & Newsome, 2014). These advancements have led to developing novel tools and technologies that provide detailed insights into neural circuits and brain function, fostering interdisciplinary collaborations and accelerating neuroscience discoveries (Rainey & Erden, 2020).

1.2.6 Advancements in neurotechnology

The deep analysis of brain signals has led to groundbreaking developments in cognitive augmentation, neurostimulation therapies, brain-computer interfaces, and neural prostheses (Cinel et al., 2019; Edwards et al., 2017; Gilja et al., 2012; Khan & Aziz, 2019). Additionally, integrating artificial intelligence with brain-computer interfaces has shown remarkable clinical success and expanded the capabilities of neurophysiological discoveries (X. Zhang et al., 2020). The advancements in neurotechnology are poised to revolutionize brain repair treatments, enhance human cognitive abilities, and shape the future of neuroscience research and applications.

1.2.7 Contribution to fields like artificial intelligence and robotics

The analysis of brain signals has significantly contributed to the fields of artificial intelligence and robotics. Integrating brain signals with artificial intelligence technologies has led to innovative applications, such as autonomous behavior, perceptual categorization, and conditioning in brain-based devices (Krichmar & Edelman, 2002). Advancements in neurotechnology have also enabled EEG signals to correct robot mistakes in real-time, enhancing the efficiency and accuracy of robotic tasks (Salazar-Gomez et al., 2017). The synergy between brain signal analysis and artificial intelligence has paved the way for transformative applications in robotics, offering new possibilities for human-robot interaction and intelligent automation.

1.3 Methods of Recording Brain Signals

1.3.1 EEG

EEG is a non-invasive electrophysiological method that records electric potentials in synchronously active neurons. EEG signals are often recorded through electrodes, usually made of silver and silver chloride, positioned on the scalp. EEG has significantly been used in clinical applications such as mental disorders diagnostics, sleep staging, and anesthesia monitoring, as well as in research settings, as a powerful toll for human brain function comprehension (Bleichner & Debener, 2017).

1.3.2 How EEG works

EEG records electrical brain activity by detecting brain wave frequencies and patterns through silver and silver chloride electrodes placed on the scalp. The process involves capturing different brain wave patterns and frequencies, providing insights into brain function and activity. EEG acquisition systems typically include scalp electrodes, amplifiers, converters, and potentially wireless transmission modules to capture and process brain electrical signals (Astrakas et al., 2012). The electrodes are usually embedded in electrode caps, often following international standards for the electrodes position in the scalp to ensure comparable and consistent results among studies, as the 10-20 international system, shown in Fig. 2, which is based on anatomical landmarks on the scalp. The distances between adjacent electrodes are 10% or 20% of the skull's total distance, front to back or left to right. Specifically, 10% is used from the anatomical landmarks and the first electrode in that direction, and 20% is used between the other electrodes. Other electrode layouts have been used following this same principle, shortening distances to efficiently capture spatial features, as in 10-10 or 10-5 systems, following the same logic and increasing the number of electrodes used. The signals acquired do not record absolute values but are relative. Two kinds of montage are used for acquiring signals: bipolar and referential. In bipolar montages, the system records the potential difference between two adjacent electrodes, with channels arranged in "chains" that can be longitudinal and transverse. These are especially useful for analyzing highly localized discharges and often present fewer artifacts than the referential. On the other hand, the referential uses one or two electrodes as a reference for all the others. The most common choice for reference placement is on the mastoid process, where, ideally, no activity can be recorded. Multiple reference electrodes can be useful in averaging their recorded values to overcome limitations such as noise, which would be picked up by one single electrode (Acharya & Acharya, 2019).

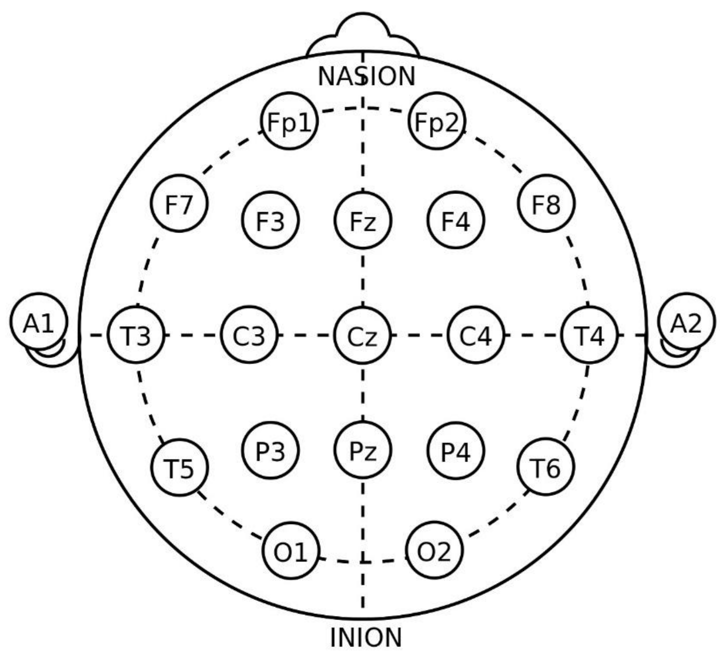

Figure 2: 10-20 International System for electrodes placement on the scalp.

1.3.3 Advantages and limitations of EEG

The main advantages of EEG include its noninvasive nature, portability, cost-effectiveness, and high temporal resolution compared to other neuroimaging techniques (Eom, 2023). The limitations of EEG include vulnerability to artifacts, the need for skilled interpretation, and potentially reduced detection with a reduced number of channels (Schultz et al., 2021). Other limitations include its current usage primarily in laboratory environments, restricting its application in real-world settings. However, some attempts to make it fit for a real-world scenario are currently being developed, such as semi-dry electrodes (Fiedler et al., 2015). Also, a significant limitation is that it can generally capture only one-third of the cerebral cortex due to spatial limitations, limiting brain activity coverage (Hasan & Tatum, 2021).

1.3.4 Other Recording Techniques

Among other recording techniques, the most relevant ones that need to be mentioned are Magnetoencephalography (MEG) and functional Magnetic Resonance Imaging (fMRI):

- MEG

MEG is a noninvasive functional imaging technique that measures the magnetic fields generated by electrical currents in the brain. Similar to EEG in multiple aspects, it proved to be especially useful in detecting areas of normal brain functions or dysfunctions (Hammond & Katta-Charles, 2016).

- fMRI

fMRI is a powerful, noninvasive neuroimaging technique that measures brain activity by detecting changes in blood oxygenation levels. It has significantly contributed to our understanding of brain function and has become popular in both clinical and research settings due to its ability to provide unique insights into brain functions. fMRI's capability of observing time-varying changes in brain metabolism has proven fundamental in many applications ranging from pharmacological efficacy to cognitive neuroscience investigations (Glover, 2011).

1.3.5 Comparison of different recording methods

EEG, MEG, and fMRI are powerful neuroimaging techniques that offer unique advantages and applications in studying brain function. EEG provides high temporal resolution, making it suitable for capturing rapid neural processes. MEG offers high spatial resolution and is valuable for precise localization of brain activity. fMRI, on the other hand, provides detailed spatial information about changes in brain metabolism. EEG and MEG techniques both rely on recording the brain's electric activity from electrodes placed on the scalp, and it appears they even hold redundant information for some applications (Murphy & Poesio, 2010). Moreover, fMRI seems to achieve better results in most of the applications thanks to the possibility of creating a tridimensional map of the activity in the brain, overcoming the limitations of EEG and MEG (Rybar & Daly, 2022), while on the other hand needing an expensive and bulky machinery to acquire the signals, making it available only in specific locations, such as hospitals.

1.4 Signal Preprocessing after Recording Brain Signals

1.4.1 Importance of Signal Preprocessing

Signal preprocessing is a critical step in brain signal analysis. Preprocessing techniques such as filtering, denoising, and artifact removal are essential for enhancing the quality of brain signals (Bashashati et al., 2007; Ergün & Aydemir, 2020). Proper signal preprocessing significantly enhances the accuracy and reliability of brain signal analysis in various applications, including BCI systems and neurophysiological investigations.

1.4.2 Enhancing signal quality for better analysis

Enhancing the quality of brain signals for better analysis involves employing various preprocessing techniques. Artifacts and noise removal play a crucial role in enhancing the quality of brain signal data by reducing interference from sources like eye blinks, EOG artifacts, EMG artifacts, and other noise sources, thereby improving the accuracy and reliability of brain signal analysis. Techniques such as spectral subtraction denoising and adaptive noise removal can effectively improve SNR (Gonzalez-Moreno et al., 2014; Kadah, 2004). These preprocessing steps play a vital role in improving the quality of brain signals for robust analysis in various applications.

1.4.3 Common Preprocessing Steps

Common preprocessing steps for brain signals typically include methods such as ensemble empirical mode decomposition, adaptive noise cancellation, deep learning denoising, and wavelet-based artifact identification (Adib & Cretu, 2013; Lin et al., 2018; Mashhadi et al., 2020; Roy et al., 2017). Employing methods like independent component analysis (ICA) and spatial filtering further enhances signal-to-noise ratio (SNR) by reducing noise interference (Lindquist et al., 2019; Um et al., 2019). Power line frequency removal, as well as this frequency's harmonics) is often performed to clean the data from further interferences. For some applications meaningful information is held within a specific bandwidth; therefore, high-pass, low-pass, and band-pass filters can be extremely useful, especially in reducing the computational load required for the analysis. These preprocessing steps are essential for enhancing the signal-to-noise ratio (SNR) and ensuring the accuracy of subsequent analyses.

- Filtering

Frequency filters commonly used in brain signal analysis include band-pass filtering at specific frequency ranges, low-pass filtering to eliminate high-frequency noise, and high-pass filtering to remove low-frequency interference. These filtering methods are crucial for preprocessing brain signals to focus on the relevant frequency components for accurate analysis (Yan et al., 2023).

- Artifact removal (eye blinks, muscle activity)

Artifact removal in brain signal analysis is crucial to ensure data accuracy, as the signal would be otherwise heavily corrupted by these sources, as shown in Fig. 3. Various methods have been proposed for artifact removal, such as using Independent Component Analysis (ICA) and Multivariate Empirical Mode Decomposition (MEMD) to eliminate EOG artifacts from multichannel EEG signals (G. Wang et al., 2016). Additionally, techniques like Singular Spectrum Analysis (SSA) combined with Independent Component Analysis (ICA) have been employed to remove diverse artifacts simultaneously from single-channel EEG signals (Cheng et al., 2019). These methods are designed to eliminate artifacts while preserving the underlying brain signals, thereby ensuring the quality and reliability of EEG data for further analysis (Junfeng Gao et al., 2010).

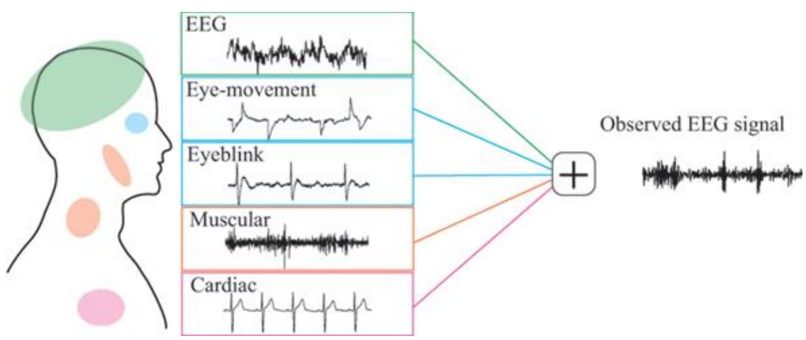

Figure 3: EEG and artifacts, the effect on the observed EEG signal (Kanoga & Mitsukura, 2017).

- Normalization and standardization

Normalization and standardization in brain signal analysis ensure data comparability and reliability. Quantitative EEG analysis offers a systematic approach to characterizing brain functions and dysfunctions, providing detailed insights into brain activity with standardized protocols (Billeci et al., 2013).

Improved normalization techniques using cohort-specific templates have been shown to enhance accuracy in normalizing lesioned brains compared to standard methods, aiding in precise brain signal analysis (Pappas et al., 2021).

1.4.4 Software tools used in preprocessing

The preprocessing of brain signals can be implemented using specific software tools. Tools like BrainNet Viewer, EEGLAB, and MNE-Python provide visualization and analysis capabilities for brain connectomics and MEG/EEG data. The BrainNet Viewer tool is commonly used for visualizing brain networks and connectivity (Xia et al., 2013). EEGLAB is an open-source toolbox for analyzing single-trial EEG dynamics, including ICA (Delorme & Makeig, 2004). On the other hand, MNE software provides comprehensive analysis tools for processing MEG and EEG data, covering preprocessing, source estimation, time-frequency analysis, statistical analysis, and functional connectivity estimation (Gramfort et al., 2013).

1.4.5 Algorithms commonly employed

The algorithms commonly employed for preprocessing in brain signal analysis include time domain filtering, blind source separation, and time-frequency domain analysis methods (Liu et al., 2017). Other techniques include simultaneous low-pass filtering and total variation denoising for EEG signals (Nimmy John et al., 2018). These algorithms are crucial in preparing brain signal data for further analysis and interpretation.

1.5 Feature Extraction in Brain Signal Analysis

1.5.1 Importance of Feature Extraction

Feature extraction is a critical step in brain signal analysis, fundamental in converting raw brain signals into meaningful information. Extracted features from EEG signals are vital for distinguishing between different brain states during tasks

(Tang et al., 2022). For example, in motor imagery tasks, these features capture important signal characteristics necessary for decoding voluntary movements and classifying cognitive states (T. Li et al., 2018).

1.5.2 Reducing data dimensionality

A fundamental aspect of feature extraction in brain signals is data dimensionality reduction. Reducing data dimensionality is essential for efficient processing and interpretation of complex data. Neural signals are naturally high-dimensional signals. The ability to extract exclusively meaningful information from the raw signals not only tends to increase the decoding accuracy but also greatly reduces the computational costs of the decoding process (Dadi et al., 2020).

1.5.3 Enhancing interpretability and analysis

As mentioned above, feature extraction also dramatically contributes to complex signals, such as brain signals, by enhancing decoding accuracy and interpretability (Dadi et al., 2020). Again, feature extraction is a fundamental step in brain signal analysis because of its many positive effects on the subsequent analysis steps.

1.5.4 Types of Features in Brain Signals

The features extractable from brain signals are many and have deep differences and meanings among each other, but most of them can be grouped into 3 classes or types: time-domain features, frequency domain features, and time-frequency domain features.

- Time-domain features

Extracted directly from the time series data, these features, such as mean, variance, skewness, kurtosis, standard deviation, zero-crossing, and peak-to-peak voltage, are directly extracted from the raw signal, providing valuable insights into signal characteristics and dynamics (Bang et al., 2013). Moreover, time-domain features can assess signal complexity through metrics like sample entropy, which reflects the irregularity and predictability of brain signals (Delgado-Bonal & Marshak, 2019). Overall, time-domain features in brain signals provide valuable information for various applications, including diagnosis, rehabilitation, and the comprehension of brain function.

- Frequency-domain features

Extracted from brain signals, these features offer insights into their frequency characteristics, providing valuable information for analysis and interpretation. The first steps most used for calculating frequency-domain features are the power spectral density (PSD) or a Fourier transform, like the Fast Fourier transform (FTT). Other than statistical features like mean, median, and variance, an important frequency-domain feature is the relative power at specific bandwidths (Stancin et al., 2021). These bandwidths have been widely studied, and the whole frequency content of brain signals has been divided into five bandwidths:

- δ (0.5 - 3.5 Hz): High-amplitude waves usually associated with the NREM sleep phase, also occur during mental calculation tasks corresponding to “internal concentration” (Fernfindez et al., 1995),

- θ (3.5 - 7.5 Hz): Theta waves are typically associated with deep relaxation and meditation. Theta waves are also thought to play a role in memory consolidation, specifically during the transition between wakefulness and sleep, in emotional processing and regulation, and in the navigation of different types of memory (Karakaş, 2020; Lagopoulos et al., 2009),

- α (7.5 – 13.5 Hz): Alpha waves represent the dominant oscillations in human brain activity and reflect a state of relaxed wakefulness. They have been shown to promote creativity and are linked with attention regulation and sensory processing (Fink & Benedek, 2014; Foxe & Snyder, 2011),

- β (13.5 – 30 Hz): Beta waves associated with active thinking are closely linked to the state of attention. Beta activity can increase in case of stress or anxious situations (Díaz et al., 2019; Hendrayana et al., 2020),

- γ (30 – 100 Hz): Gamma waves have been observed during tasks requiring high cognitive processing and attention (Koelewijn et al., 2013). They appear to play a role in controlling synchronization between different brain regions, contributing to various complex processes such as movement, perception, and memory (Guan et al., 2022).

Frequency domain features are essential for tasks like emotion recognition, fault diagnosis, and EEG signal classification, enabling a comprehensive analysis of brain signals in various applications.

- Time-frequency domain features

The analysis of brain signals simultaneously in the temporal and frequency domains is a powerful tool for observing the change in frequency over time. Short-time Fourier transform (STFT) and Wavelet transform are the main functions used to calculate these features (Stancin et al., 2021).

1.5.5 Methods for Extracting Features

Different methods are applied to perform feature extraction of different features from raw data. Most of these methods can be categorized into one of the following methods groups: statistical methods, machine learning techniques, and entropy-based methods.

- Statistical methods

Statistical methods, used for both time-domain and frequency-domain features, encompass extracting features based on statistical properties and methods to characterize the data utilizing statistical characteristics like mean, variance, skewness, kurtosis, standard deviation, and more (Stancin et al., 2021).

- Machine learning techniques

Machine learning techniques for feature extraction use algorithms and models that can automatically identify and extract meaningful patterns from the raw data. These techniques are especially suitable for handling complex, high-dimensional data such as brain signals. Among the most used techniques, we can mention Principal Component Analysis (PCA) and ICA, machine learning algorithms that divide the data into different components based on the most significant variance and source components, respectively, as well as Convolutional Neural Networks (CNNs), that aim at extracting more abstract features from the data through the application of multiple convolutional layers, and Recurrent Neural Networks (RNNs), particularly useful to capture temporal dependencies in sequential time-series data by maintaining a memory of previous inputs (Jogin et al., 2018; Keren & Schuller, 2016; Khalid, 2014).

- Entropy-based methods

Entropy-based methods quantify the complexity, irregularity and unpredictability of a time series of data. These methods have been widely used to analyze dynamic and non-linear data. Some examples of entropy-based methods are Shannon's entropy, which quantifies the amount of information held in stochastic data, and spectral entropy, which quantifies the complexity or randomness of a signal in the frequency domain (Garcia-González et al., 2023; A. Zhang et al., 2008).

In the next chapter, we will explore semantic features, one of the most important aspects of brain signals. Understanding these features is crucial for advancing our brain-to-brain communication, artificial intelligence, and cognitive neuroscience knowledge.

Chapter 2: Semantic Feature Extraction from EEG Signals

2.1 Introduction to Semantic Features in EEG Signals

Semantic features are the essential components of the meaning that a lexical item, like a word or a sentence, holds. These components represent the characteristics of a specific term or sentence and allow us to differentiate meanings and define relationships between different lexical items.

2.1.1 Definition of semantic features in the context of brain signals

Semantic features in the brain refer to the distinct attributes and characteristics that our brain uses to encode and represent meaning in language and concepts. These features are derived from the patterns of neural activity observed during cognitive processes involving understanding, processing, and generating language. By analyzing these patterns, researchers can identify specific neural correlates associated with different semantic elements, thereby shedding light on how the brain organizes and accesses meaning. This understanding is crucial for advancements in brain-to-brain communication, artificial intelligence, and cognitive neuroscience (Fuseda et al., 2022; Gao et al., 2019).

2.1.2 Importance and Potential Applications

The study of semantic features in brain signals is a burgeoning field with great potential to unravel how our brain represents concepts and information. This field of study can provide fundamental insights into how the brain not only represents but also organizes and retrieves semantic information to develop better models of our cognition and memory systems and create better maps of our brain through the identification of the brain regions involved in semantic features processing, as well as increasing our ability to diagnose and treat language-related disorders. The potential applications of semantic features are countless and range from education and learning systems based on individual neural responses to mental health diagnosis and therapy in atypical semantic-related conditions such as aphasia, to neuromarketing, to the great improvement of BCIs and neurorehabilitation technologies, to artificial intelligence, and to the creation of technologies that would allow us to have direct brain-to-brain communication.

2.1.3 Current Research Landscape

The current research landscape for semantic features in brain signals is growing and encompasses various studies focusing on decoding semantic information from neural activity. Studies have utilized multivariate pattern analysis and representational similarity analysis to investigate how the brain represents semantic content (Liuzzi et al., 2020). Research has shown that semantic features are retained as neural oscillations and play a role in memorization processes (Noguchi, 2022). Additionally, efforts have been made to map semantic representations in the brain, linking concepts with specific brain areas based on shared semantic features (L. Zhang et al., 2019). These studies highlight the ongoing exploration of how semantic features are processed and represented in the brain, shedding light on the intricate mechanisms underlying semantic cognition.

Existing research on semantic features in brain signals highlights how, with time, our comprehension of how our brain holds semantic features significantly improves. To assess the hypothesis under which semantic features are represented with specific patterns of neural activations, researchers succeeded in classifying the brain signals from stimuli given through different modalities, such as visual and auditory (Simanova et al., 2014). Another similar study was performed between visual perception and imagery mechanisms as stimulus modality, suggesting that the semantic

features could be best observed in the parieto-occipital cortex and the α frequency band (Dijkstra et al., 2019; Xie et al., 2020).
Additionally, attempts have been made to predict neural activations occurring from stimuli given in a language by prior analysis of the neural activity in reaction to the same stimuli provided in a different but similar origin language (Van de Putte et al., 2018). These studies confirm that while part of the neural activation is due to the stimuli modality, which elicits different neural processing pathways, part is linked to the semantic concept.
Studies have shown that EEG responses can reflect the retrieval of lexical semantic information (Bastiaansen et al., 2008), the integration of semantic information during language comprehension (Sarett et al., 2023), and predict emotional states (Deniz et al., 2019; Gao et al., 2019). Additionally, both spatial and temporal analysis of EEG signals have been shown to provide crucial information (Chan et al., 2011).

While some efforts have been made, many aspects of semantic features still need to be discovered. The techniques and methods used until now shed light on many truths, but simultaneously realized the difficulties on this topic. We know that semantic processing involves multiple brain regions, but the exact interaction mechanism between them remains largely unclear. The representation of semantic features also presents a vital inter-subject and even intra-variability due to different factors that can be both environmental and depend on the personal history and experience of each subject, even, for example, their sex and age.

Therefore, exploring semantic features is of the utmost importance and will require many studies, each focusing on different aspects and possible approaches.

This section will focus on the possibility of semantic feature extraction from EEG signals, one of the most versatile and cost-effective brain signal acquisition technologies that could be the key to implementing many real-life applications.

2.2 EEG Relevancy towards Semantic Feature Extraction

EEG signals possess several properties that make them particularly relevant for semantic feature extraction. These properties include:

- High Temporal Resolution: EEG signals are characterized by their high temporal resolution, typically milliseconds. This allows for the precise tracking of neural dynamics as they unfold in real time, making it possible to capture rapid changes in brain activity associated with semantic processing.

- Frequency Band Analysis: EEG signals can be decomposed into different frequency bands associated with distinct cognitive and physiological states. For example, Delta (0.5-3.5 Hz) is often linked with deep sleep and unconscious processes; Theta (4-7 Hz) is associated with drowsiness, meditation, and memory encoding; Alpha (8-13 Hz) is related to relaxed wakefulness and inhibition control; Beta (14-30 Hz) relates to active thinking, focus, and alertness; and Gamma (>30 Hz) is tied to high-level cognitive functions, such as perception and consciousness. Each of these bands can provide different insights into the neural correlates of semantic processing, helping to differentiate between various semantic features based on their frequency-specific activity.

- Spatial Resolution: Although not as high as some other neuroimaging techniques like fMRI, EEG provides adequate spatial resolution using multiple electrodes placed on the scalp. This spatial distribution allows researchers to infer the involvement of different cortical regions in semantic processing. Advances in source localization techniques, such as Low-Resolution Brain Electromagnetic Tomography (LORETA), have improved the spatial interpretability of EEG data.

- Non-Invasiveness and Practicality: EEG is a non-invasive method used in various settings, including clinical, research, and everyday environments. Its portability and relatively low cost make it accessible for widespread use, facilitating large-scale studies on semantic feature extraction.

- ERPs: EEG can measure ERPs, which are time-locked responses to specific stimuli. ERPs such as the N400 and P600 components are particularly relevant to semantic processing. The N400 is associated with meaning processing and is sensitive to the semantic congruence of words within a context, while the P600 is linked to syntactic processing and reanalysis.

- Neural Oscillations and Synchronization: EEG allows the study of neural oscillations and their synchronization across different brain regions. Oscillatory activities have been implicated in binding semantic features and integrating information across distributed neural networks, especially in the theta and gamma bands.

- Neuroplasticity and Learning: EEG can capture changes in brain activity associated with learning and neuroplasticity. As semantic knowledge is acquired and refined, EEG can track how neural representations of semantic features evolve over time, providing insights into the dynamic nature of semantic processing.

By leveraging these properties, researchers can employ EEG to decode the neural underpinnings of semantic features, enhancing our understanding of how the brain processes, organizes and retrieves semantic information.

2.3 The Concept of Entropy in Signal processing

Entropy is a fundamental concept in thermodynamics and information theory, representing a system's degree of disorder or randomness. In the context of EEG signals, entropy represents a measure of irregularity or unpredictability in the signal, offering valuable insights into the underlying brain activity. Various entropy measures can be computed from EEG signals to capture distinct aspects of signal complexity (Sharma et al., 2015). Among the many entropy measures used, some of the most important ones are Shannon entropy, spectral entropy, approximate entropy, sample entropy, permutation entropy, and multiscale entropy.

It's important to note that rigorous data preprocessing is always necessary to obtain accurate and meaningful entropy measures. Preprocessing includes power-line noise removal via notch filtering to remove power-line frequency and its harmonics. A high-pass filter is often applied to EEG signals to filter out frequencies below 0.5 Hz to remove low-frequency drifts due to head movements, wires, and scalp perspiration. As entropy measures are prone to numerical instability with very small values, a normalization or standardization step is crucial for their correct implementation. A low-pass filter is often applied to keep meaningful information while rejecting mainly artifacts and noise. A high-pass filter with a cut-off frequency of 2 Hz can be applied to obtain high-quality ICA decomposition for artifact removal. ICA efficiently removes artifacts such as blinks, eye movements, and muscle activity. Eye components can be identified with other tools to obtain epochs around EOG events, which are then rejected by the ICA (Wilson et al., 2023).

2.3.1 Entropy Measures in EEG Analysis

Among the various entropy methods available, each possessing unique strengths and weaknesses, this study will concentrate on Shannon entropy, spectral entropy, sample entropy, permutation entropy, and multiscale entropy. A brief overview of each of these entropy measures will be provided:

- Shannon Entropy (H): Introduced by Claude Shannon, Shannon entropy quantifies the average uncertainty in a set of possible outcomes. For EEG signals, Shannon entropy can measure the unpredictability of neural activity, offering insights into the brain's information processing capacity. The implementation for Shannon entropy is typically expressed as:

$$H(x) = -\sum_{x \in X} p(x) * log_2 p(x) \qquad (1)$$

where:

- H(x) denotes the entropy of the source “x”,
- x is the set of all the possible outcomes of the random variable,
- p(x) is the probability mass function, which represents the probability of each outcome occurring,
- the negative sign is used to ensure the obtained value is always non-negative.

This formula quantifies the average amount of information a stochastic source produces, providing a measure of its predictability.

Shannon entropy has found numerous applications in many different fields. In the EEG context, it has been applied in the diagnosis and classification of neurological disorders, such as in Alzheimer's disease research, underscoring the significance of its measures, or in the diagnosis of autism spectrum disorder (Abásolo et al., 2006; Djemal et al., 2017). It has even been used and proven crucial to distinguish between focal and non-focal EEG signals (Sharma et al., 2015).

- Spectral Entropy (SE): Derived from the signal's power spectral density, it measures the distribution of power across frequency bands, indicating the complexity of the frequency components of EEG signals. The spectral entropy value indicates how evenly the power is distributed across the frequency spectrum, with higher entropy values suggesting a more uniform distribution and lower entropy values indicating a more concentrated power distribution within the signal.

  The implementation for spectral entropy consists of calculating the entropy of a signal's power spectral density (PSD). The formula can be expressed as:

$$SE = -\sum_{i=1}^{n} \left(\frac{P(f_i)}{P_{total}}\right) \log \left(\frac{P(f_i)}{P_{total}}\right) \tag{2}$$

where:

- SE represents the spectral entropy,
- $P(f_i)$ is the power at frequency f_i,
- P_{total} is the total power of the signal,
- n is the total number of frequency bins.

Various studies have leveraged spectral entropy in different EEG applications. It has been suggested as a biomarker for altered function in conditions like schizophrenia and bipolar disorder, where abnormalities in entropy modulation of the EEG signal have been identified (Molina et al., 2020). Spectral entropy has also been employed in classifying EEG suppression to assess the risk of sudden unexpected death in epilepsy (SUDEP) (Mier et al., 2020). Moreover, spectral entropy has been applied in identifying brain regions affected by bipolar disorder, demonstrating its utility in highlighting impaired brain regions in such conditions (Khaleghi et al., 2019).

- Sample Entropy (SampEn): An improvement over approximate entropy, Sample Entropy is less dependent on data length and excludes self-matches, making it more reliable for analyzing EEG signals. Sample entropy can be considered as an evolution of approximate entropy. Used to quantify the complexity and unpredictability of time-series data, same as approximate entropy, it offers numerous advantages. Sample entropy has also been found to be more sensitive to EEG phase changes, exhibiting higher relative separation rates than other entropy measures, including approximate entropy (Khaleghi et al., 2019; Y. Li et al., 2022).

  The implementation for sample entropy involves calculating the negative natural logarithm of the conditional probability that two sequences of data, each of length "m", similar within a tolerance "r", will remain similar when their length is increased by one data point. The formula for sample entropy can be expressed as:

$$SampEn(m, r) = -ln\left(\frac{A(m+1, r)}{A(m, r)}\right) \tag{3}$$

where:

- $SampEn$ represents the sample entropy,
- m is the length of the sequences to be compared,
- r is the tolerance parameter that defines similarity between data points,
- $A(m,\ r)$ is the number of similar sequences of length m with tolerance r.

Studies have demonstrated the efficacy and potential of sample entropy for many applications, such as capturing variations in brain activity related to attention or as distinguishing patterns linked to epilepsy. Many studies emphasized sample entropy's versatility and effectiveness in extracting valuable information from EEG signals (Song & Liò, 2010; P.-S. Wang et al., 2014).

- Permutation Entropy (PE): Assesses the complexity of a time series based on the order of its values, capturing non-linear and dynamic properties of EEG signals. It quantifies the irregularity and predictability of a time series based on the order in which values appear. Higher permutation entropy values indicate greater complexity and randomness in the time series, while lower values suggest more regular and predictable patterns (Bandt & Pompe, 2002). Compared to others, permutation entropy shows simplicity and efficiency, with a notable robustness to noise. Additionally, it can capture non-linear and non-stationary characteristics of time series that other more traditional entropy measures might miss.

  The implementation for permutation entropy involves calculating the Shannon entropy of the probability distribution of ordinal patterns in the time series. The formula can be expressed as:

$$PE = -\sum_{i=1}^{m!} p_i \log(p_i) \quad (4)$$

where:

- PE represents the permutation entropy,
- $p(x_i)$ is the probability of occurrence of the "i"th permutation pattern in the time series,
- m is the embedding dimension,

- The sum is taken over all $m!$ possible permutations of the signal components

Permutation entropy has been widely used to analyze EEG signals across various fields, such as sleep stages, anesthesia, epilepsy, and meditation (Nicolaou & Georgiou, 2011; Zhu et al., 2017).

- Multiscale Entropy (MSE): Evaluates the complexity of time-series data across multiple time scales, providing a more comprehensive understanding of signal dynamics. The specific implementation for multiscale entropy may vary depending on the approach used, such as multiscale sample entropy or multiscale dispersion entropy (Rossini et al., 2020).

The implementation of Multiscale entropy is based on the specific approach, as it calculates a different entropy, such as Shannon or sample entropy, at different time scale. It is implemented, for a generic entropy En, as:

$$MSE(\tau) = EN\left(y^{(\tau)}\right) \tag{5}$$

where:

- MSE represents the multiscale entropy,
- τ is the temporal scale factor that defines the length of the non-overlapping windows,
- EN is the generic entropy method implemented for the specific application of multiscale entropy,
- $y^{(\tau)}$ is the “Construct Coarse-Grained Time Series, it is a new time series of data created by averaging the data points within non-overlapping windows of data points, defined as:

$$y_j^{(\tau)} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} x_i \tag{6}$$

with $j = 1,2,\dots,\left[\frac{N}{\tau}\right]$.

Multiscale entropy has been used to analyze brain signals and assess cognitive decline in conditions like Alzheimer's disease (Azami et al., 2017). The versatility of multiscale entropy makes it a powerful tool for characterizing the complexity and dynamics of diverse systems across different temporal scales.

2.3.2 Application in EEG Signal Analysis

- Feature Extraction: Entropy measures are used to extract features that capture the inherent complexity of EEG signals. These features can differentiate between different mental states or cognitive tasks.
- Detection of Abnormalities: In clinical settings, entropy can identify abnormal brain activities such as epileptic seizures. Lower entropy values may indicate the highly ordered structure of seizure activity, while higher values correspond to normal brain function.
- BCIs: Entropy measures enhance BCI performance by providing robust features that improve the classification accuracy of user intentions, making BCIs more effective and responsive.
- Cognitive State Monitoring: Entropy analysis helps in monitoring cognitive states such as attention, relaxation, and workload, which are essential for applications in neurofeedback and cognitive training.

2.3.3 Quantifying Dynamic Complexity

- Neural Dynamics: EEG signals exhibit dynamic complexity due to the brain's non-linear and non-stationary nature. Entropy provides a framework to quantify this complexity, revealing how different brain regions interact over time.
- Temporal Variability: By analyzing entropy over time, researchers can understand how brain activity fluctuates during different cognitive processes or states, offering insights into the temporal dynamics of neural activity.

2.3.4 Challenges and Considerations

- Data Quality and Noise Sensitivity: Entropy measures can be sensitive to noise and artifacts in EEG data. Proper preprocessing, such as filtering and artifact removal, is crucial for accurate entropy calculation. Since entropy measures the uncertainty in a probability distribution, any distortion, such as noise and outliers, can lead to incorrect entropy values. Redundancies in the data can also alter entropy measures by artificially increasing the regularity of a series. Moreover, small sample data can lead to significant statistical fluctuations, making entropy measures unreliable. All these potential issues can heavily impact entropy measures. Many studies assessed how data quality is most important for accurate entropy estimations (Grenn et al., 2015; Zanin et al., 2012).

- Parameter Selection: The accuracy of entropy measures depends on the selection of parameters like embedding dimension and tolerance in Sample Entropy or the scale factor in Multiscale Entropy. Careful tuning of these parameters is necessary to obtain meaningful results.
- Computational Complexity: Efficient algorithms and computational resources are required to handle large EEG datasets. The computational complexity and challenges of implementing entropy methods can vary depending on the specific application and the type of entropy measure utilized. Entropy methods are often

applied to high-dimensional data, and data points can become sparse, making it difficult to estimate probability distributions accurately. Entropy calculations also often involve logarithms and small probabilities, which can lead to numerical instability. Additionally, approximate and sample entropy have high computational costs due to their reliance on many data points (Lu et al., 2017).

- Interpretation of the Results: Interpreting the results obtained from entropy measures can present several challenges due to the data's complexity and nature. Like the EEG signals, they are calculated from entropy measures influenced by the dataset's context, environment, or other specific characteristics. This aspect and others, such as the scale and range of the data, can present challenges when compared to different datasets, increasing the difficulty of getting to an absolute interpretation. Entropy measures can be applied to perform temporal and spatial analyses. In both cases, interpreting the results can be quite challenging given the high dimensionality of the data and its susceptibility to many factors. Additionally, different entropy measures produce different results with the same data, each with its own interpretation and applicability, and that can lead to further confusion when trying to interpret many entropy measures together (Hu, 2017; Mammone et al., 2011).

By leveraging entropy measures, researchers can gain deeper insights into the complexity and dynamics of brain activity.

2.3.5 Tools and Software

Finding applications in multiple fields, entropy measures have gained extensive interest. Many tools and software incorporated the calculation of such measures, and where missing, first-party and third-party toolboxes filled the gap. Two main programming languages have been widely employed in research environments: MATLAB and Python.

MATLAB has a built-in function, “wentropy,” which computes various signal entropy measures. Available toolboxes for entropy calculations are “Signal Processing Toolbox” and “Wavelet Toolbox,” which provide various functions for many time-frequency analyses, filtering, and more, including entropy calculations. EEGLAB is also an interactive MATLAB toolbox for advanced EEG and MEG analysis.

In Python, many libraries are available to calculate entropy measures. Libraries like SciPy, NumPy, PyEntropy, antropy, nolds, mne-python, and others offer the possibility of calculating various entropy measures, with each library filling the gaps of the others, covering different possibilities for entropy calculations.

2.4 Case Studies and Real-World Applications

Entropy measures are not new in many fields but represent a novel approach to semantic feature extraction from EEG signals. Despite its newness, some studies and real-world applications are already available. This section will briefly overview some of these studies and applications to prove the potentialities and interests surrounding entropy-based methods.

Case Study 1:

This study is an example of how an entropy measure was used to successfully extract semantic features from EEG signals. In 2022 a group of researchers proposed their newly developed entropy method, the multivariate multiscale modified-distribution entropy (MM-mDistEn) to perform emotion recognition from multichannel EEG signals. Emphasizing the need for multichannel EEG rather than relying only on one or two channels, they assessed the classification capabilities of features extracted with MM-mDistEn. An Artificial Neural Network, trained with backpropagation, was used for classification of the two classes: valence and arousal.

The architecture was tested with 2 different datasets: the “Database for Emotion Recognition System Based on EEG Signals and Various Computer Games” (GAMEEMO) and the “Database for Emotion Analysis using Physiological Signals” (DEAP). They achieved classification performances of 95.73% ± 0.67 for valence and 96.78% ± 0.25 for arousal for the GAMEEMO (Fig.4) dataset, and of 92.57% ± 1.51 in valence and 80.23% ± 1.83 in arousal for the DEAP dataset (Fig.5) (Aung et al., 2022).

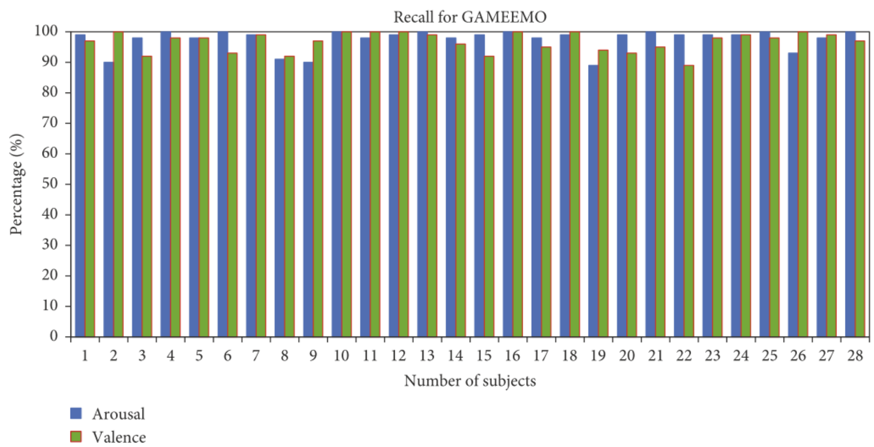

Figure 4: Performances on the GAMEEMO dataset (Aung et al., 2022).

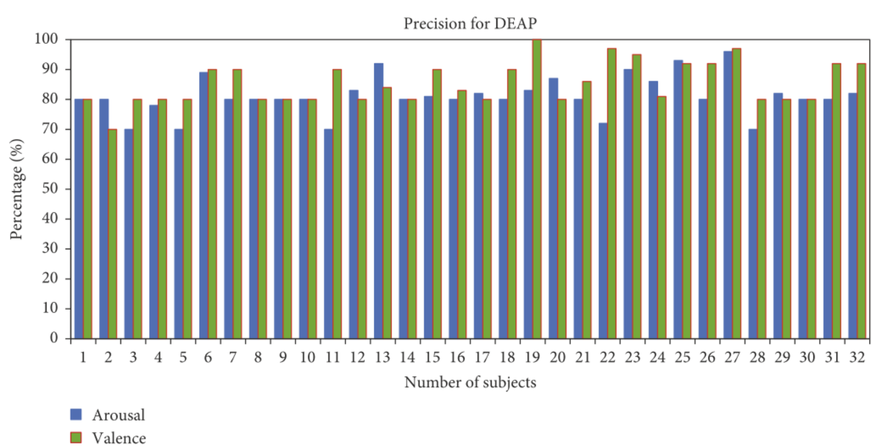

Figure 5: Performances on the DEAP dataset (Aung et al., 2022).

Case Study 2:

This study highlights the practical use of entropy measures. In (Mu et al., 2017), the authors used multiple entropy measures, such as spectral entropy, approximate entropy, fuzzy entropy, and sample entropy, to detect driver fatigue, a major cause of traffic injuries. As in the real application, some electrodes would record mainly noise; therefore, Fisher distance was used to measure electrode selection. Support Vector Machine (SVM) was the machine learning algorithm used for the classification. This study's average classification accuracy of 98.75% emphasizes how the extracted features from the electrodes T5, TP7, TP8, and FP1 may yield better performance. In Fig.6, it is possible to visually notice the difference between the normal and fatigue states using fuzzy entropy. In this study, entropy measures have been shown to hold great potential for feature extraction from EEG signals.

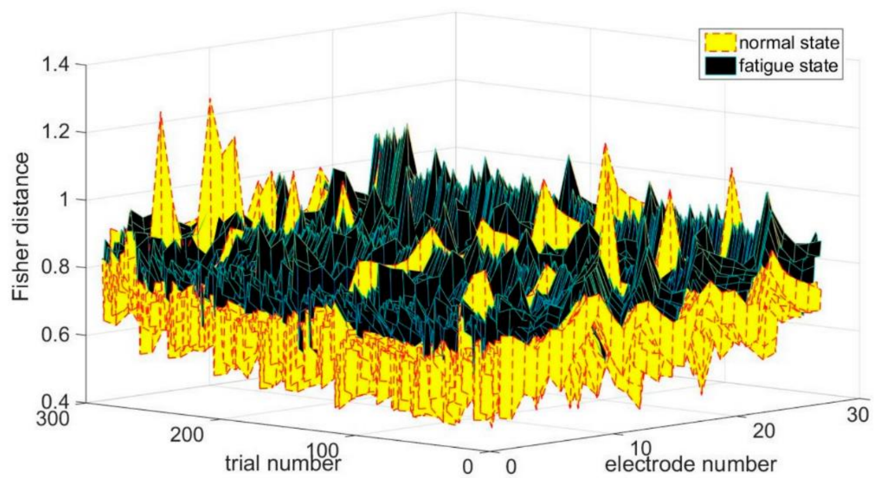

Figure 6: Comparison of Fisher distance on fuzzy entropy across multiple samples in two states (Mu et al., 2017).

Real-World Applications:

Entropy methods find many real-world applications. Approximate and sample entropy are used in epilepsy detection devices, as EEG loses complexity during seizures. Entropy measures are even used for early detection and monitoring of neurodegenerative diseases such as Alzheimer's disease and dementia. They're used to monitor the depth of anesthesia during surgeries and to provide additional data for depression and anxiety diagnosis. Additionally, control systems use entropy measures for BCIs to improve accuracy and reliability of signal interpretation (Liang et al., 2015; Zambrana-Vinaroz et al., 2022).

2.5 A Comparative Analysis between Entropy Measures and Other Feature Extraction Methods

Among the various techniques available to perform feature extraction from brain signals, entropy measures surely stand out for their ability to focus on the complexity or unpredictability of the data. Even so, every technique presents its advantages and disadvantages therefore other features are often utilized. Time-domain features are always appreciated for their simplicity and ease of implementation and interpretation, especially compared to entropy measures. On the other hand, they often struggle with noise sensitivity and, due to their simplicity, can easily miss more complex patterns present in dynamic and high-dimensional data like EEG signals. Frequency-domain techniques transform time-series data to the frequency domain, revealing hidden periodic components and filtering noise. Despite their positive characteristics, they can be computationally intensive and result in an important loss of temporal resolution. Time-frequency domain provide a more balanced approach by analyzing the signal in both time and frequency domain simultaneously. They provide a dynamic analysis of the data but can significantly increase computational complexity and may require attentive parameter tuning to optimize the process. Entropy measures often show promising results where other techniques struggle, being able to distinguish between two time-series data with similar temporal and frequency characteristics, focusing on their information content and complexity. Due to their nature, compared to other techniques they tendentially lack in temporal resolution by providing a single value calculated oven a sequence of data points and, additionally, can pose to serious challenges for their interpretation. Some entropy methods, like approximate and sample entropy, can also be quite computationally heavy, making these not optimal for real-time applications with the current computational power. Given these disadvantages, it's crucial to remember that they offer a completely different point of view on the data while also being relatively robust to noise. Entropy measures can successfully distinguish subtle differences in patterns that other methods might miss and are especially fit to capture the non-linear dynamics of a signal providing insights into complex and high-dimensional data. Moreover, techniques such as Multiscale Entropy allow for the analysis of complexity and unpredictability of a signal at multiple temporal scales, potentially providing additional meaningful information (Ljung & Glover, 1979; Stancin et al., 2021).

2.6 Chapter Summary and Preview

Knowing what semantic features are in the context of EEG signals and the attempts made for their extraction, it's clear that our knowledge in the field is still limited and that exploration possibilities are countless. Entropy measures have already been used to perform feature extraction from brain signals both in clinical and research settings, with some real-life applications as well, but there are very few studies that attempted to apply them to perform semantic feature extraction. Other techniques, such as time-domain, frequency domain, and time-frequency domain, have been used to perform semantic feature extraction, but entropy techniques can offer a different point of view for data analysis and interpretation. There are indeed many challenges regarding both the means, entropy methods, and the goal, semantic feature extraction, but, as in many novel studies, the potentialities overcome the difficulties.

A robust methodology, justified by what is reported above, is crucial to obtaining significant results from a study involving entropy measures of EEG signals in an attempt to extract semantic features. Every step, if rigorously taken, can greatly enhance the outcomes.

The next chapter will describe the methodology, including details on the dataset specifications, preprocessing steps, the types of entropy measures used, and the rationale behind these choices. It will outline the methods and approaches employed, setting the stage for the subsequent presentation of results in a dedicated section.

Chapter 3: Materials and Methods

3.1 Dataset

The dataset used in this study has been made available by the authors of (Wilson et al., 2023). This dataset was chosen for the analysis for its pertinence with this study, offering the possibility of studying different concepts expressed in different modalities and for their dimension as one of the few relatively extended datasets available online involving semantic concepts. The dataset comprises the EEG signals acquired by twelve subjects, three of which performed more than one session. One participant with visual and hearing impairment was included in the study. Before the experiment the subjects completed 2 questionnaires, the Bucknell Auditory Imagery Scale (BIAS-V)(Halpern, 2015) and the Visual Imagery Questionnaire (VVIQ) (Isaac A. et al., 1986), that served as reports of, respectively, auditory and visual mental imagery ability. The questionnaire scales are 1 to 7 for BIAS-V and 1 to 5 for VVIQ. The questionnaire resulted in an average of 4.76 for the BIAS-V and 3.75 for the VVIQ.

3.1.1 Experimental Procedure

After the questionnaires and a practice session, the subjects could ask questions about any uncertainties. The procedure for the actual experiment follows the main task flow presented in Fig. 7. The experiment was designed using *Psycophy Version 3* (Peirce et al., 2019), presented on a 1920x1080 resolution screen, and performed with environmental lights off. A Lab Streaming Layer network sent the triggers to acquire timestamps related to the stimuli given by the presentation. The experiment consisted of 10 blocks, but most of the participants stopped before the end due to fatigue or reduced concentration (Wilson et al., 2023).

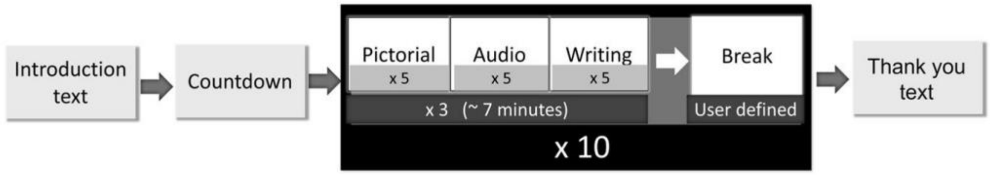

Figure 7: This figure shows an example of a trial. Five trials occur after a cue indicating the stimuli modality, each with a different stimulus. The subject decides the break duration (Wilson et al., 2023).

3.1.2 Data Acquisition

For data acquisition, a *128 channel ANT Neuro eego Mylab* measuring system with 124 EEG electrodes was used. The gel-based cap of the electrodes has active shielding, offering protection from 50/60 Hz environmental noise. The sampling rate was 1024 Hz with a 24-bit resolution. The electrodes were placed following the 10-5 International System. The EEG cap size was chosen based on the participant's head circumference, which was large, medium, and small. OneStep Cleargel conductive gel was applied to the electrodes referenced to CPz. The ground was fixed to the left mastoid with Ten20 paste. The goal was to obtain an impedance of below 50, but due to individual factors, often up to 10 electrodes had higher impedance. The EEG data was stored as *.cnt* files and the events as *.evt* files in ANT Neuro native format (Wilson et al., 2023).

3.1.3 Paradigms

The dataset is based on six paradigm variations consisting of two tasks: imagination and perception, and three modalities: pictorial, orthographic and auditory comprehension. Three semantic categories were used: guitar, flower and penguin. These concepts were selected due to their semantic distance, determined by computing a Word2Vec latent space (Mikolov et al., 2013), so that all pair-distances were <0.2 (Fig. 8). For the perception task the authors used different pictures varying between simple, intermediate and complex style, for the pictorial task, different fonts and colors for the orthographic task, and 2 seconds long clips varying between low, medium and high voice for the auditory comprehension task. The imagery tasks took place after the perception's, leaving to the subject the task of imagining what they had seen/heard. In the pictorial task, the image in the perception task appears in a white box, that appears again in the imagery task to frame the mental image. In the orthographic task the text is presented on a white square background that also appears in the imagination task. A representation of an example trial can be observed in Fig.9 (Wilson et al., 2023).

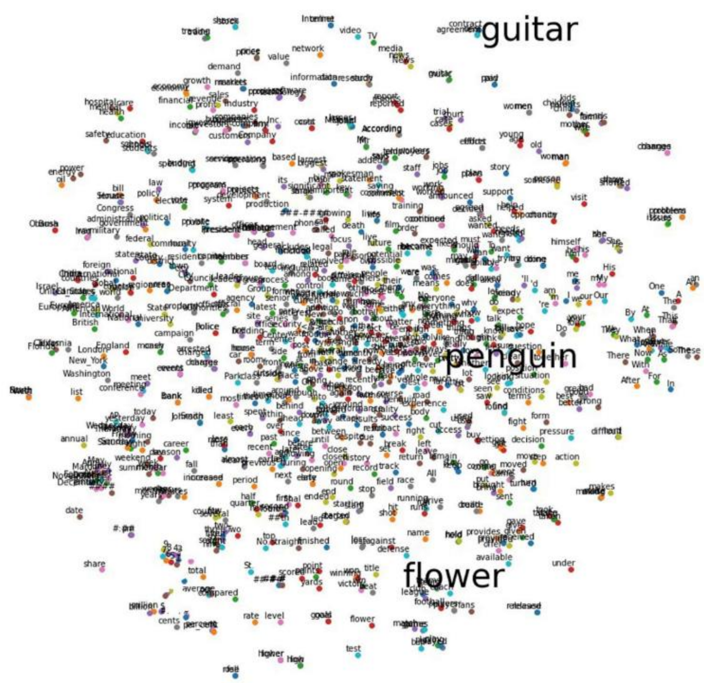

Figure 8: 2D plot, using a t-distributed Stochastic Neighbor Embedding (t-SNE), of semantic distances computed using Word2Vec (Wilson et al., 2023).

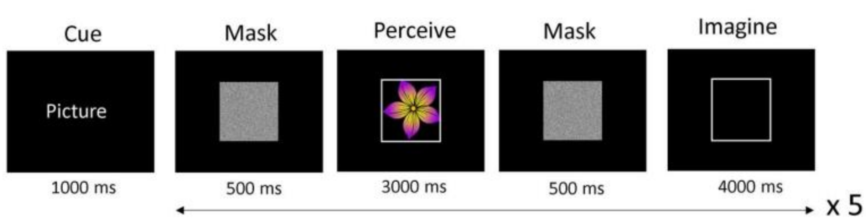

Figure 9: Example of a pictorial trial. After the cue, 5 trials occur with a different picture in each (Wilson et al., 2023).

3.2 Preprocessing

The dataset consists of two subsets: raw data and preprocessed data. Since the preprocessing performed by the dataset authors aligns with this study's objectives, the preprocessed data was used. This study details the specific preprocessing steps completed by the dataset authors and those conducted during this research. The bad channel detection and interpolation, re-reference of the electrodes, the Notch filtering, the high-pass filtering, and the ICA application were performed by the dataset's authors. The bad channel detection and interpolation, described in section 3.2.1, was fundamental to obtaining clear data and meaningful results from all the epochs as a bad channel could record low quality signal or missing signal altogether, missing a large portion of the underlying brain activity (Courellis et al., n.d.). The Notch filtering wouldn't have been strictly necessary for this study, as the highest frequency analyzed was 30 Hz of the β waves, but it didn't affect the signal analyzed, so it was negligible. On the other hand, the high-pass filtering was necessary for correctly applying the ICA application, crucial for artifact removal in the signal analyzed. Therefore, preprocessed data was used to incorporate these crucial steps, bad channel interpolation, and artifact removal, into the dataset, which would have required considerable time and resources to apply to the whole dataset due to manual resource limitations. This section provides a detailed description of all the preprocessing methods applied to the raw dataset.

3.2.1 Data Processing

The first preprocessing step performed by the authors was bad channel detection. Both manual and automatic detection were performed. Automatic detection was performed using PyPrep PrepPipeline, which uses several bad channel detection methods, such as the correlation between channels, channels with abnormally high or low amplitudes, and channels with flat signals. Interpolation was then applied to correct these channels. A re-reference step to CPz electrode was performed after every step that offset the statistical trend of the overall data. It was applied before and after bad channel interpolation and after filtering to remove low-frequency drifts. Re-referencing was computed through common average referencing in MNE (Wilson et al., 2023).

3.2.2 Filtering

Notch filtering removed power-line noise at 50 Hz and its harmonics. A high-pass filter with a cutoff frequency of 2 Hz was applied to remove low-frequency drifts, such as head movements and skin perspiration, and to perform high-quality ICA decompositions. Artifact removal was performed via ICA's application. The FastICA algorithm was used, and 50 components were selected. Eye components were identified using an MNE-implementation that generates epochs around EOG artifacts, estimated from Fp1 and Fp2 electrodes.

In this study α and β bandwidths were analyzed; therefore, an additional band-pass filter had to be applied, with cutoff frequencies 7.5 Hz and 13.5 Hz for α, and 13.5 Hz and 30 Hz for β, to isolate these bandwidths from the rest of the signal and allow for specific analysis. The low-pass section of the band-pass filters also removed higher-frequency noise. This choice was made to observe the characteristics of different bandwidths in detail, and due to the limited resources and time, we focused on specific ones. Many studies pointed out different frequencies performing better for semantic extraction, suggesting meaningful semantic information could be held from θ to γ waves. The choice was made following (Klimesch et al., 1997; Pfurtscheller & Kumesch, 1992) but that doesn't imply the absence of semantic information at lower or higher frequencies. The band-pass filter was implemented using a Butterworth filter (Farah Binti Hussin et al., 2016). The filter parameters were calculated with the “butter” from *scipy* library. The filter was applied through the “sosfiltfilt” fuction, also from *scipy* library. This method was picked to perform zero-phase filtering while maintaining numerical stability.

Additionally, data was downsampled from 1024 Hz to 256 Hz to reduce the computational load without altering the observations.

All the preprocessing steps performed on the data have been applied with the Python coding language. Specifically, the preprocessing performed in this study has been coded on Google Colab, and the data is stored on Google Drive. The data was uploaded first to Google Drive in a *.fif* format, as shared by the authors, and then loaded on Google Colab. The data was then extracted with the "read_raw_fif" function from *mne* library.

3.3 Entropy for Semantic Feature Extraction in EEG signals

3.3.1 Rationale

Chapters 1 and 2, highlighted the lack of semantic feature extraction from EEG signals and the potentiality of entropy measures. This study proposes to evaluate the potentiality of certain entropy measures in the context of semantic feature extraction in EEG signals. This approach was chosen after carefully considering the most used features for semantic feature extraction in EEG signals and their limitations. Due to the great inter and intra-subject variability of EEG signals, an approach based on the "information theory" (Shannon, 1948) could bypass this issue by analyzing the quantity of information developed in different brain regions, potentially picking up patterns that would be ignored by other methods. As brain activity, when processing any kind of information, displays an increase in activity and irregularity, an approach able to pick on that increase in complexity could be crucial for semantic feature extraction. Different entropy measures have been implemented based on their approach to quantifying the complexity or randomness of a signal. Shannon entropy, spectral entropy, sample entropy, permutation entropy, and multiscale entropy were implemented, each quantifying the complexity of a signal with different approaches. The entropy measures implemented were chosen among others to observe how their different approaches would perform in this specific task. Specifically, Shannon and spectral entropy differ from the data utilized to calculate the entropy, where Shannon uses the original time-series data while spectral entropy uses the power spectral density of the data. Assessing which one would look more promising was crucial to understand which path was more convenient to follow, the time-domain or the frequency-domain related entropies. Also, thanks to their easy implementation, they work as a “base” for many entropies, and their results can direct our interest towards a specific category of entropy measures rather than others. Permutation entropy and sample entropy were chosen due to their similar base concept but different approaches: permutation entropy's approach is based on the “order” of data points, calculating the probability of that order being preserved by shuffling data points in a small time window, while sample entropy's key concept is the “similarity”, looking for similarities in nearby data points, even if not in the exact order. An important difference is that permutation entropy looks for exact matches, while sample entropy includes a tolerance variable, making it more noise-resistant. Additionally, sample entropy was selected over approximate entropy due to its proposed crucial advantages, highlighted in section 2.3.1. Finally, multiscale entropy analysis is crucial because it does not consider the signal as one single block but effectively divides it into time windows, allowing finding patterns restricted in specific moments after the stimuli onset. These entropy measures have been selected to provide a general overview of the possibilities entropy measures offer and assess what approach is more promising for differentiating semantic features.

To assess the possibility of performing semantic feature extraction through entropy measures, they were computed over each electrode. Theoretically, each concept should be represented by different brain activity patterns, therefore impacting different electrode recordings. A statistical analysis will be later implemented to assess the difference between the concepts.

3.3.2 Implementation

For the calculation of entropy measures, data was loaded differently based on the task: imagination or perception. Following the specifications in the experiment modality in section 3.1.3, the imagination tasks were cropped from the stimuli onset to 4 seconds afterward, while the perception tasks were cropped to 3 seconds after the stimuli onset. The entropy measures were calculated at different moments, dividing the dataset into five subsets, mainly for resource limitations. This division step was performed so that, as 3 participants took part in a second experimental session, it was equally divided to grant different subjects for each subset, avoiding a subset containing data from more experiments from the same subject. Also, each subset contained up to 1-second session to ensure variability between the data and maximize similarity across subsets.

After each entropy calculation, a normalization step was computed over the whole subset to ensure comparability and correct analysis interpretation for further steps.

- Shannon Entropy

Shannon entropy was calculated by computing the probability distribution over a histogram that divided values into intervals. The number of intervals, or bins, was set to 50. The rationale behind this choice was to keep the number of bins above the value provided by the square-root method (square root of data points) to obtain a relatively detailed view of the data and not oversimplify the analysis of high-complexity EEG signals. A value was obtained for each electrode for the whole epoch.

- Spectral Entropy

Spectral entropy was implemented using the Welch method (Welch, 1967). The "welch" function from the *scipy* library calculates the signal's power spectral density. The result is then normalized over the sum of each element to represent a probability distribution. A histogram, with the number of bins equal to 50 as above, was then applied to perform the entropy calculation. Each electrode was then assigned a value for the epoch.

- Sample Entropy

Sample entropy was computed with the “sampen” function from *nolds* library. Similarly to before, each electrode was assigned a value representing the whole epoch's activity.

- Permutation Entropy

Permutation entropy was computed using the “permutation_entropy” function from the *ordpy* library. Again, a value was assigned to each electrode for each epoch.

- Multiscale Entropy

Thanks to its features, multiscale entropy was implemented based on Shannon entropy, with different time scales. The data was analyzed in non-overlapping time windows of 250 ms and 500 ms, respectively, 64 and 128 samples, considering 256 Hz of the signal. Differently from other entropies, for each epoch, each electrode was assigned an array of values representing the different time window entropies.

3.4 Visual and Statistical Analysis

Each entropy's results were analyzed through different means to investigate their potentiality for classification.

3.4.1 Visual Analysis

Across the concepts (guitar, flower, and penguin), visual analysis was performed on all entropies, multiscale excluded due to the results format. A 2D plot of the scalp and a histogram were selected to perform this analysis to make it possible to observe the spatial representation and the occurrences distribution of the entropy measure's results, respectively.

A 2D plot representing the scalp with a color-graded electrode value was computed by averaging the electrode values across the epochs. The coordinates of the electrodes necessary for the plot were obtained from the "get_elec_coords" function, using the electrode names available in the *.fif* file and the placement layout used, and plotted with the "plot_coords" function. Both functions are part of the *eeg_positions* library. To transform normalized values to colors, a "ScalarMappable" object from the *matplotlib* library was generated and then used for the conversion with the ".to_rgba" property of the object. The color map used was "viridis". The color bar was added with the function "colorbar" again from the *matplotlib* library. Additionally, a histogram, computed with the "hist" function from the *matplotlib* library, was plotted to observe concept similarities or abnormalities.

3.4.2 Statistical Analysis

All entropy measures were subject to statistical analyses. Specifically, the Analysis of Variance (ANOVA) and the T-test were implemented. The statistical analysis images shown in Chapter 4 were generated on *Matlab* with "Statistics and Machine Learning Toolbox".

- ANOVA

  ANOVA is a statistical method used to compare the means among more than 2 different groups and assess whether at least one group is statistically different from the others. This statistical analysis chose ANOVA due to its renowned efficiency and flexibility. ANOVA considers the differences between and within the groups, making it a perfect instrument for this specific analysis.

  ANOVA was implemented on the entropy measures across epochs of each electrode to assess which electrode could perform better at discriminating among concepts. ANOVA returns F-scores, Fisher-Snedecor distribution-derived values calculated as the ratio of the mean square variance between groups (MSB) and mean square variance within groups (MSW),

$$F = \frac{MSB}{MSW} \tag{7}$$

and negative log of p-values, negative logarithm in base 10 of the p-value:

$$-\log_{10}(p) \tag{8}$$

representing the probability of the null hypothesis, the hypothesis that there is no difference between the groups, being true. A significant value for the p-value is usually set around 0.1 or 0.05 or smaller, which corresponds to a negative log of p of 1 or 1.3 or higher (Anders, 2017). ANOVA method was implemented with the function "f_classif" from *sklearn* library.

- T-test

  A t-test is a statistical method used to determine whether there is a statistically significant difference among 2 groups. After applying ANOVA, looking for the statistical difference of one of the groups from the others, the natural following step was to look for statistical differences between each pair of the groups to assess if each can be considered statistically differentiated from the other. To do so, the t-test was chosen for its ease of interpretation, as it is a straightforward method that compares the mean of 2 groups to determine if they differ from each other.

It was applied, similarly to ANOVA, among epochs for each electrode, but this time, all possible pairs of concepts were compared: guitar and flower, guitar and penguin, and flower and penguin. If the p-value obtained is below a statistical level α, usually set around 0.1 or 0.05, then the null hypothesis is rejected. T-test was conducted with Bonferroni correction for multiple analyses. Bonferroni correction is a statistical adjustment applied when multiple comparisons are being conducted to minimize the probability of a type I error, the rejection of a null hypothesis that is true, occurring. It adjusts the significance value based on how the number of conducted comparisons as:

$$\alpha_0 = \frac{\alpha}{number\ of\ comparisons} \tag{9}$$

For example, with 124 electrodes being analyzed and α of 0.05, the new α_0 would be 0.403×10^{-3} (Sedgwick, 2012; Tae Kyun Kim, 2015). For the t-test, only electrodes that achieved statistical significance were saved. T-test was implemented with "ttest_ind" function from *scipy* library.

Chapter 4: Results

In this section results will be presented. As many of these, especially regarding the visual analysis, strictly refer to images, and due to the excessive number of images across different groups obtained from the different methods, not all will be presented. Some images will be presented for context and clarification, but the results will be mainly exposed textually.

4.1 Visual Analysis Results

The visual analysis interpretation found constants between the different entropy measures and bands. While concept differentiation could be somewhat appreciated across various groups, histogram interpretation led to no results, showing some slight differences in kurtosis and skewness of the histogram curve, but so slight and apparently random that no assumption was made. An example will be presented in the paragraph showing greater differentiation to highlight the issue.

- Shannon entropy

    - α band

      In the α band some differences could be generally appreciated. In some case the distinction was evident, while in others it would be still present but less evident, relying on the scale more than on the colors (Fig. 10).

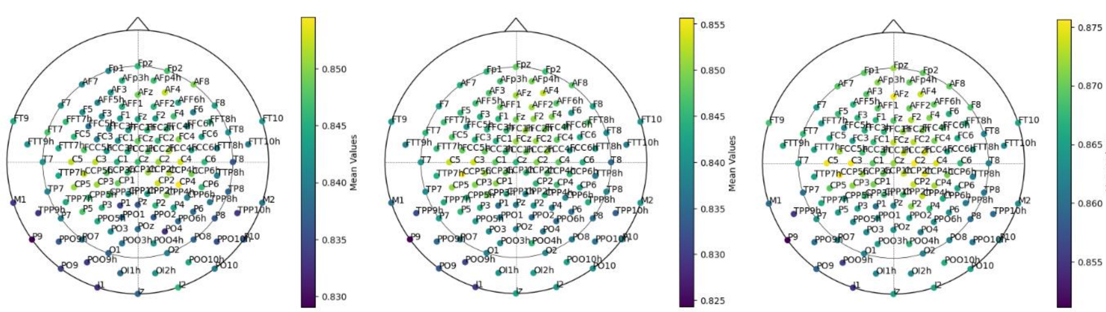

Figure 10: 2D plot of Shannon entropy in alpha waves for, in order, guitar, flower and penguin. Group 1.

- β band

In the β band differences could be hardly appreciated, with some rare and slight difference in a couple of groups (Fig. 11).

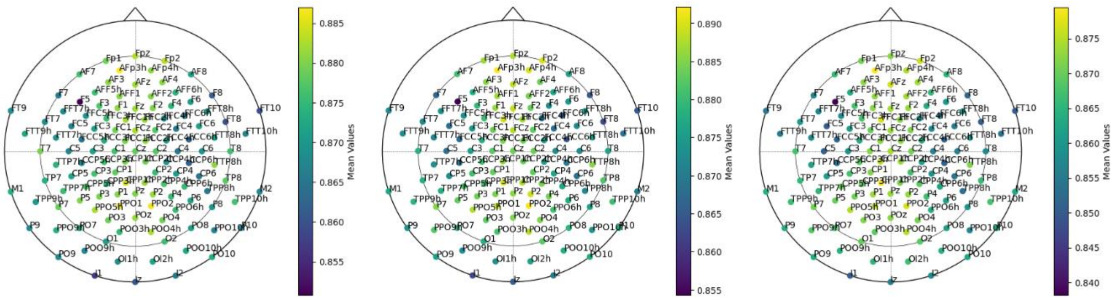

Figure 11: 2D plot of Shannon entropy in beta waves for, in order, guitar, flower and penguin. Group 3.

Overall, Shannon entropy showed some potential for distinction of the concepts in the α bandwidth, while showing little to no evidence in the β bandwidth.

- Spectral entropy

In spectral entropy no meaningful difference could be observed between the concepts in any of the groups in both α waves, as shown in Fig. 12, and β waves, in Fig.13.

- α band

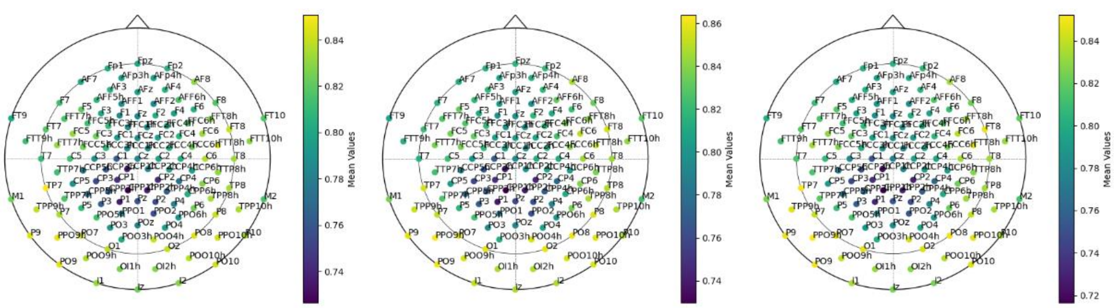

Figure 12: 2D plot of spectral entropy in alpha waves for, in order, guitar, flower and penguin. Group 4.

- β band

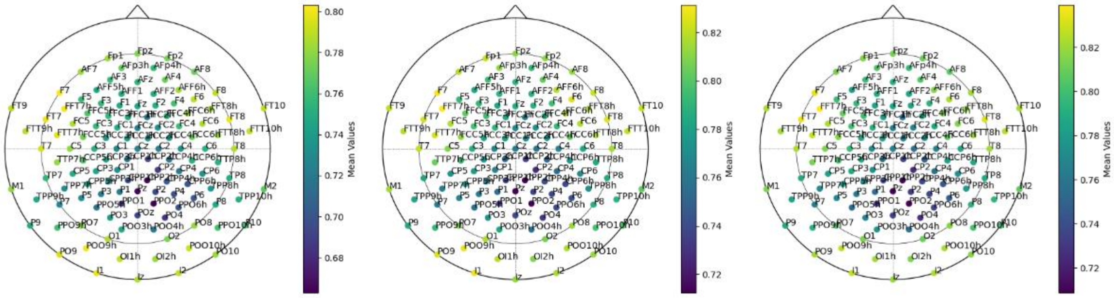

Figure 13: 2D plot of spectral Shannon entropy in beta waves for, in order, guitar, flower and penguin. Group 1.

- Sample entropy

  - α band

Sample entropy showed the greatest potential among the entropies visually tested. Particularly in the α band the differences between concepts are appreciable in Fig. 14. Additionally, as mentioned above, the related histograms will be presented in Fig. 15 to support the judgement of no evident differentiation between concepts.

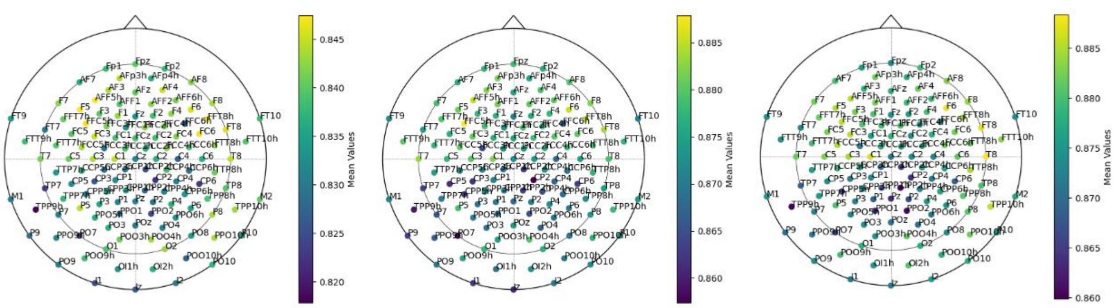

Figure 14: 2D plot of sample entropy in alpha waves for, in order, guitar, flower and penguin. Group 5.

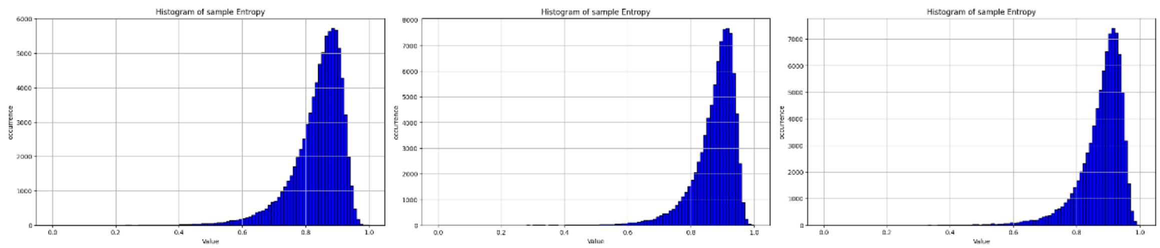

Figure 15: Histogram of sample entropy in alpha waves for, in order, guitar, flower and penguin. Group 5.

- β band

In the β band sample entropy shows some slight differences (Fig.16). Not as appreciable as in α waves, but still more evident than Shannon entropy in the same bandwidth.

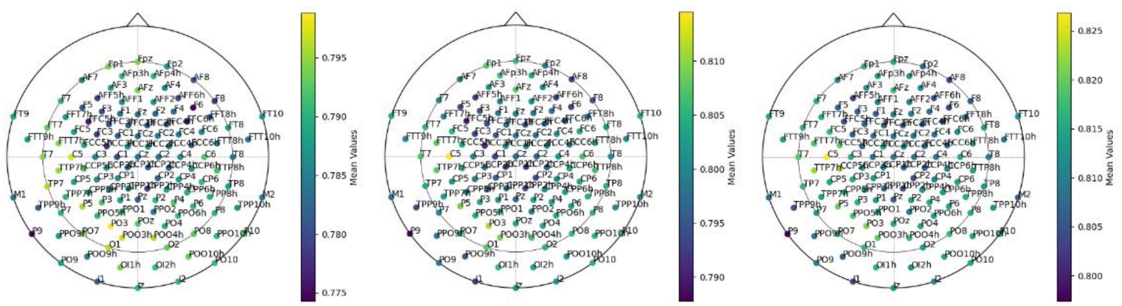

Figure 16: 2D plot of sample entropy in beta waves for, in order, guitar, flower and penguin. Group 1.

Overall, sample entropy showed the greatest differences among the concepts in the various groups.

- Permutation entropy

Permutation entropy showed no sign of differentiation between concepts in α (Fig.17) and in β waves (Fig.18).

- α band

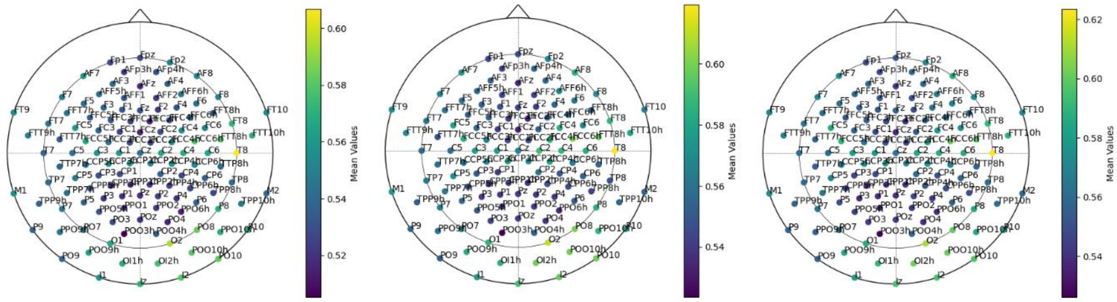

Figure 17: 2D plot of permutation entropy in alpha waves for, in order, guitar, flower and penguin. Group 2.

- β band

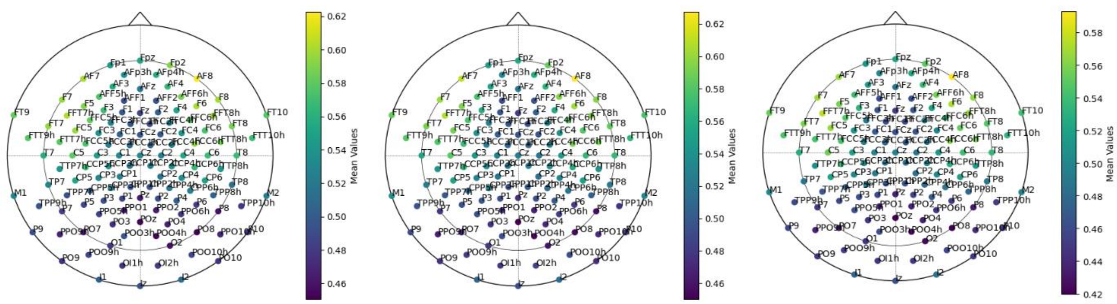

Figure 18: 2D plot of permutation entropy in beta waves for, in order, guitar, flower and penguin. Group 3.

4.1 Statistical Analysis Results

To effectively represent a huge amount of data and ensure clarity, the following images will represent, across the various groups, the number of electrodes with a significant p-score ($p<0.05$).

- ANOVA Results

  - α band

ANOVA results for α band suggest Shannon entropy and sample entropy as holding more potentiality for semantic concept differentiation, with generally higher and more constant results coming from sample entropy.

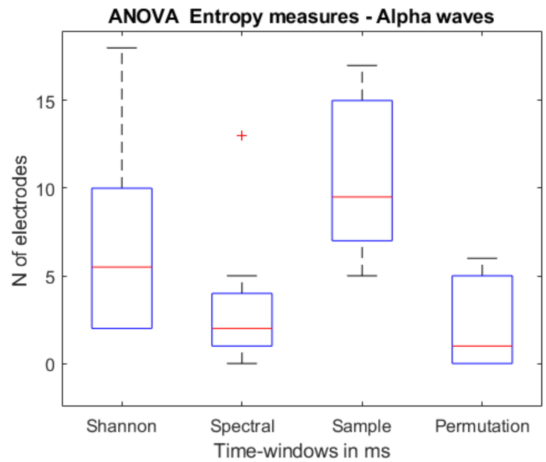

Figure 19: Number of electrodes with a statistically significant p-score across groups with different entropy measures computed in alpha waves

In multiscale entropy different time windows seem to perform better than others as a sort of "wave pattern" can be observed, reaching for higher values in the first time windows, then going down to grow again towards the end of the signal analyzed.

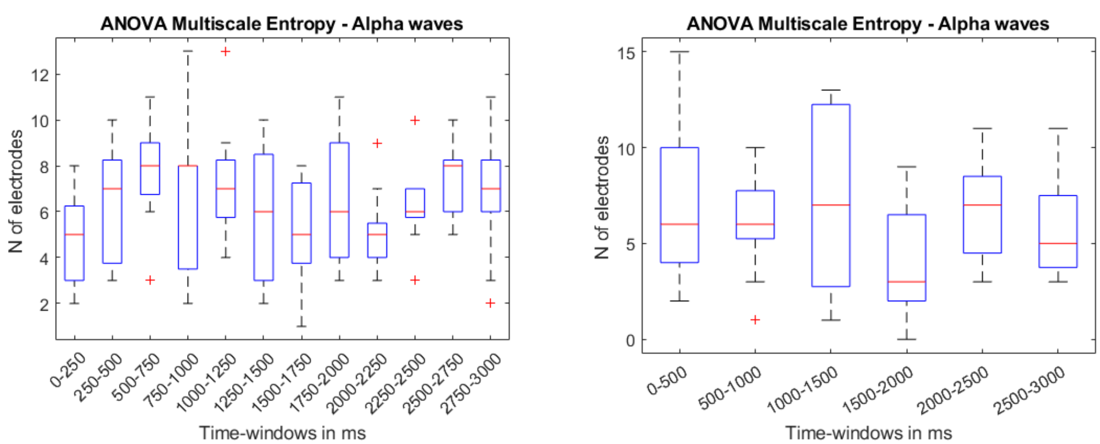

Figure 20: Number of electrodes with a statistically significant p-score across groups with multiscale entropy with different time scales and windows computed in alpha waves

Particularly, in multiscale entropy with a 500ms time scale this tendency can be observed in Fig. 21, where global and local maximums often appear, respectively, within the first 1500ms and in the last 1000ms:

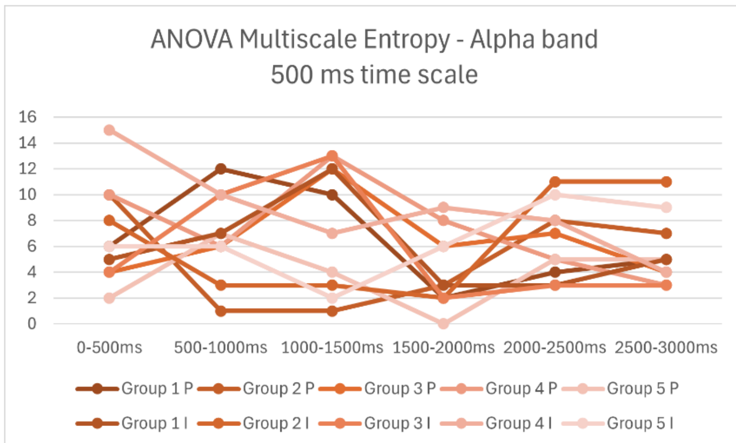

Figure 21: Line plot of the number of electrodes with a statistically significant p-score across groups with multiscale entropy at 500ms time scale computed in alpha waves, where "P" indicates perception tasks and "I" imagination tasks.

- β band

In the β band ANOVA results suggested slight better but variable results coming from sample entropy, while Shannon entropy lacked the same consistency as in the α band.

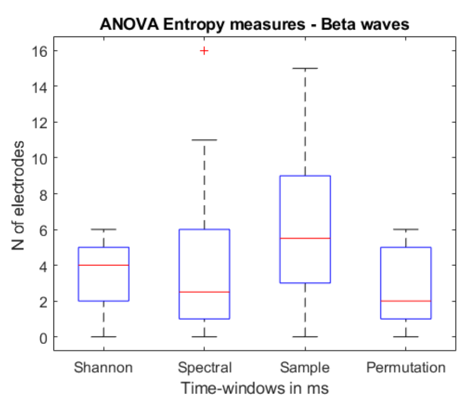

Figure 22: Number of electrodes with a statistically significant p-score across groups with different entropy measures computed in beta waves

No tendency was observed regarding multiscale entropy in the β band, suggesting poor semantic meaningful information held in such frequency bandwidth.

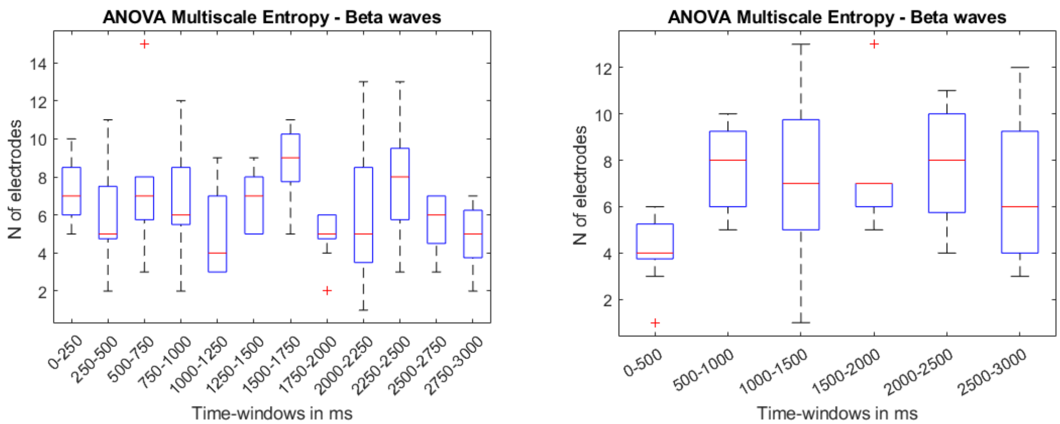

Figure 23: Number of electrodes with a statistically significant p-score across groups with multiscale entropy with different time scales and windows computed in beta waves

Something peculiar can also be observed in β waves as in most of the groups spectral entropy performed greatly better in imagination tasks, suffering majorly only in group 3.

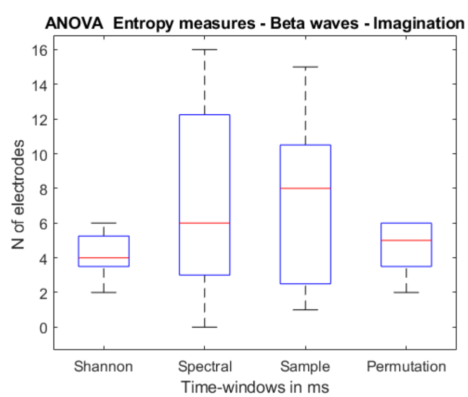

Figure 24: Number of electrodes with a statistically significant p-score across groups with different entropy measures computed in beta waves in Imagination tasks

- T-test Results

  All t-test were implemented with Bonferroni correction to limit type 1 error in multiple comparisons.

  - α band

For the different entropy measures t-test can provide a general idea of the situation, but it's obvious that some issue lies within the results. Part of the results for some groups indicated 0 or 124 significant electrodes, possibly indicating the occurrence of type 1 and type 2 errors, often including, but sometimes rejecting all the electrodes values. While still taking this issue into account, tendentially the results tend to align with the ANOVA test in this case.

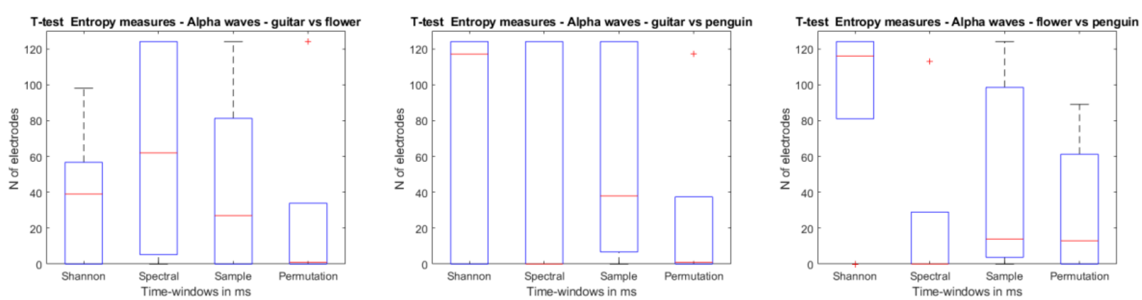

Figure 25: Number of electrodes with a statistically significant p-score across groups with different entropy measures with different time scales and windows computed in alpha waves. Respectively: Guitar vs Flower, Guitar vs Penguin, Flower vs Penguin.

For multiscale entropy only an example has been brought of T-test as, probably due to the low number of samples, it would perform extremely high or extremely low, with rare exceptions. This is probably due to the nature of Shannon entropy used in the multiscale implementation, as with a low number of samples, given the signals were resampled to 256Hz, would be limited in the possible number of results, especially in the first case.

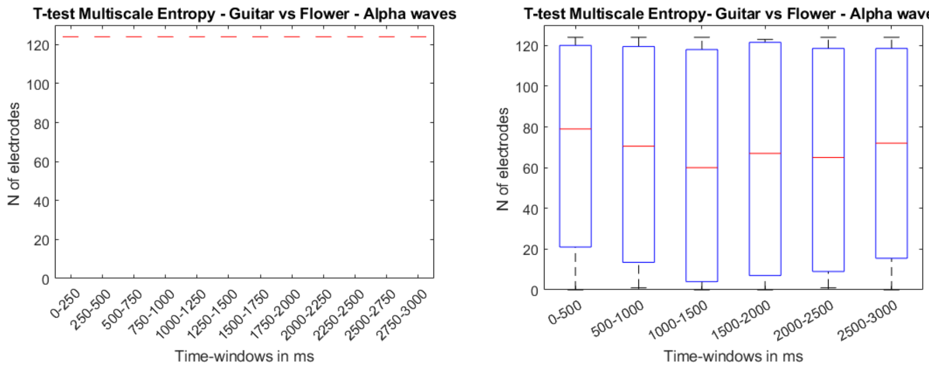

Figure 26: Number of electrodes with a statistically significant p-score across groups of multiscale entropy measures computed in alpha waves. Respectively with a time scale of 250 and 500ms.

To support this interpretation, the distribution of the values measured by multiscale entropy in the 2 scenarios is displayed in Fig. 27, where the difference is appreciable.

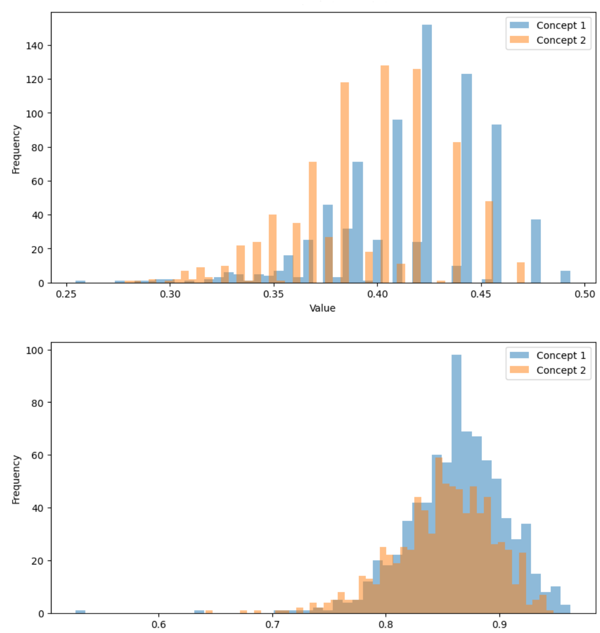

Figure 27: Distribution of multiscale entropy values alpha waves. Respectively, in the time windows 0-250ms and 0-500ms. Concept 1 is Guitar and Concept 2 is Flower.

- β band

The issue persists even in the β waves but again, generally, the results outline sample entropy better performances.

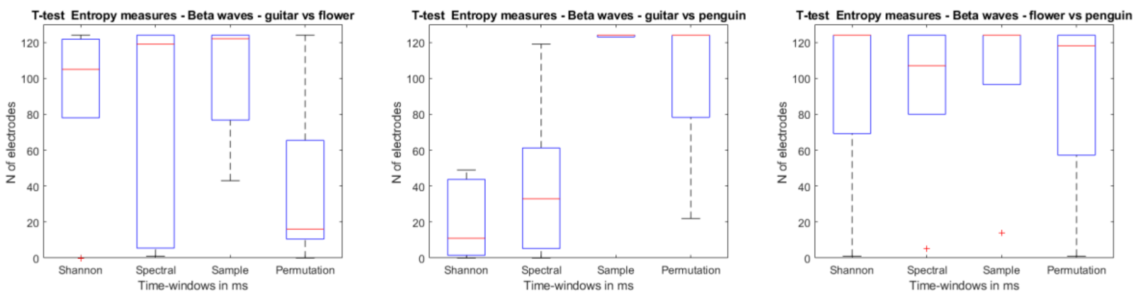

Figure 28: Number of electrodes with a statistically significant p-score across groups with entropy measure computed in beta waves. Respectively: Guitar vs Flower, Guitar vs Penguin, Flower vs Penguin.

Multiscale entropy shows similar results to the α waves and is probably affected by the same issues.

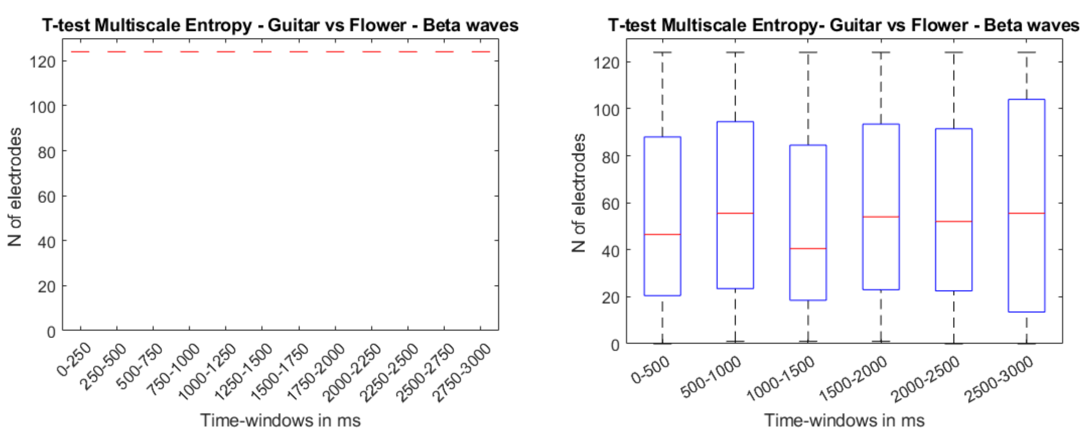

Figure 29: Number of electrodes with a statistically significant p-score across groups of multiscale entropy measures computed in beta waves. Respectively with a time scale of 250 and 500ms.

Chapter 5: Discussion

This study aims at evaluating the potentiality of certain entropy measures for differentiation between semantic concepts in α and β waves. From the results obtained in Chapter 4 a few considerations can be made.

Foremost, the t-test showed important issues in its application, probably mainly due to its susceptibility to Type 1 and Type 2 errors, even with Bonferroni correction, making it significantly less interpretable compared to ANOVA testing, which limits these issues by controlling the overall error rate and the comprehensive use of data. Therefore, towards the interpretation of the results, it will be used only for support for some general interpretation, preferring ANOVA as a more reliable source of information towards a more accurate understanding. Additionally, the discussion of the results will separate multiscale entropy from the others as specific considerations should be made.

Out of the visual and statistical analysis, a trend for interpretation can be noticed. Shannon entropy and sample entropy showed better potentiality for differentiation, with a partial indication for spectral entropy utility from the ANOVA test in imagination tasks in the β waves, and a poor contribution of permutation entropy, possibly due to its nature of searching for exact patterns in the context of a high-complexity signal. Regarding Shannon entropy, better results were achieved in the α waves, while showing comparable to spectral and permutation entropies in the β waves. Even sample entropy, even if showing better results compared to Shannon entropy, obtained a significantly outcome in the α waves. It should be noted also that, while outperforming other entropy measures, sample entropy presents a computational cost significantly greater than other methods. The potentiality of Shannon entropy and sample entropy depend on the specific application. For real-time applications where the computation needs to be completed in the shortest possible time Shannon entropy might be the right choice. For different applications sample entropy seems to hold a greater potential and with proper resources it could provide valuable information.

Multiscale entropy, differently from the other methods, doesn't calculate a single value for the whole epoch, but divides the signal into time-defined windows, possibly providing additional information regarding the evolution of the brain activity at different moments. For the tests performed in this study multiscale entropy was implemented through Shannon entropy, therefore its results should be compared to Shannon entropy results. Some considerations should be made before giving a judgement on multiscale entropy potentiality. Referring to Fig. 21 the results suggest a tendency, or pattern, in which most of the global maximums of number of statistically significant electrodes appear within the first 1500ms and another local maximum after 2000ms. Given that the results come from different groups composed of different subjects and trials the results are an average of the samples considered. Hypothetically, aligning these patterns could possibly represent a significant approach to improve performances. This pattern, if confirmed and further explore by other studies, could offer insights into how our brain elaborates semantic information. In general, compared to Shannon entropy, multiscale entropy showed a slight improvement in α waves and a significant one in β waves. An important limitation of multiscale Shannon entropy, as reported in Chapter 4, is the limited possible values that can be obtained from a short signal. This issue is strictly related to Shannon entropy and another kind of entropy not affected by this issue such as sample entropy could be implemented, with the downside of the computational load in this specific case. As the tests were conducted with Shannon entropy the results of the ANOVA test for multiscale entropy could have been in fact limited, especially in the 250ms time window. Generally, multiscale entropy seems to hold great potential for its application as it has been able to significantly improve the results in the β band, but towards a possible application into a semantic features extraction algorithm the right considerations and data manipulations should be used to maximize its potential. Which specific time scales and windows are most effective for semantic concept differentiation is still unknown, with just a few directions highlighted in this study that could be further explored in future studies.

Moreover, α bandwidth has shown to hold more meaningful information that makes it possible to differentiate between semantic concepts compared to the β bandwidth, in accordance with the literature (Klimesch et al., 1997).

Due to resources limitations using Google Colab the dataset had to be divided in multiple groups and, for some tests like ANOVA, imagination and perception tasks were analyzed separately to reduce the computational cost. While still having a significant number of samples for any participant, having only 3 subject per group might have created imbalances and important differences across the groups, which could have affected the results. Multiscale entropy was evaluated with Shannon entropy rather than sample entropy mainly for this reason as, due to the time required, Google Colab would often disconnect before completing the analysis. This limitation also affected the frequency bandwidths observed, as the initial scope was to provide a complete overview of the entropy measures possibilities in different bandwidths.

Future studies should address these issues by exploring even other promising frequency bandwidths, such as θ and γ. Additionally, performing classification using the insights from this study could shed light on the actual applicability of entropy measures towards semantic features extraction. Multiscale entropy could have many applications, therefore studies aiming at finding the best parameters to obtain meaningful results are crucial, as well as developing a tailored classification algorithm that would focus on its specific features to optimize the outcome.

Chapter 6: Conclusion

This study aimed at exploring a field still largely unknown, proposing a first step for future research regarding the use of entropy measures as a tool to perform semantic feature extraction from EEG signals analyzing α and β waves.

To summarize the results and their interpretation, Shannon entropy and sample entropy seem to hold greater potential for semantic concept differentiation compared to spectral entropy and permutation entropy, especially in the α bandwidth where significant better results were achieved overall. Spectral entropy showed some limited but interesting results in the β waves relative to imagination tasks. Multiscale entropy, on the other hand, offers to apply such entropies to specific time windows and represents a promising approach that, with the right algorithm, could significantly impact semantic feature extraction research. Multiscale Shannon entropy showed limitations regarding its calculation for small time windows related to the number of samples, simultaneously suggesting the presence of a tendency for better performing time windows, opening to possibility for specific research around certain moments rather than analyzing the whole signal, possibly impacting accuracy of classification and computational costs.

Despite the limitations of this study, the insights can have an important role in for understanding strengths and weaknesses of promising entropy measures, as well as some possible uptakes for the design of a CNN or RNN specifically tailored to perform semantic feature extraction through entropy measures.

To assess the validity of this study, as one of the first steps in this direction, more studies will have to be conducted focusing not only on expanding the exploration to other frequency bands and methods, but also on empirically test semantic feature extraction with entropy measures confirm or deny not only the results regarding what entropy measures would perform better, but also the considerations made analyzing the results such limitations and trends.

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