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Abstract

This paper introduces a novel application of Tsallis entropy for complexity analysis in electroencephalography (EEG) data. Tsallis entropy, a generalization of Shannon entropy, is employed to uncover hidden structures and distinguish varying complexity levels in EEG signals. By leveraging this framework on publicly available EEG datasets, the study demonstrates that Tsallis entropy is highly effective in categorizing brain activity patterns across different levels of complexity. The results highlight the method's potential for clinical and experimental neurodata analysis.

Keywords: Tsallis entropy, electroencephalography, EEG, time series, complexity analysis

1 Introduction

Electroencephalography (EEG) is a widely used technique for measuring electrical activity in the brain, providing valuable insights into neurological processes. Traditional methods like Shannon entropy capture general patterns but may fail to reveal the full complexity of EEG signals. Tsallis entropy, a generalization of classical entropy, offers a more nuanced view by adjusting for non-extensive behaviors in the data. This paper explores the application of Tsallis entropy to EEG data, aiming to better characterize the complexity of brain activity through time series analysis.

2 Methodology

2.1 Tsallis Entropy

Tsallis entropy is given by the formula:

$$S_q = \frac{1}{q-1}\left(1 - \sum_i p_i^q\right) \tag{1}$$

where:

- p_i is the probability of occurrence of the value i in the time series.
- q is the Tsallis entropy parameter, which adjusts the sensitivity of the measure to the probability distribution.

For the special case where $q = 1$, the formula reduces to Shannon entropy:

$$S_1 = -\sum_i p_i \log(p_i) \tag{2}$$

Tsallis entropy adjusts classical entropy by introducing a parameter q that controls the weight given to different probabilities. This allows the entropy to account for non-extensive systems, where the behavior of the whole is not merely the sum of its parts, making it particularly useful in complex systems like the brain.

2.2 Data Preprocessing

Before calculating Tsallis entropy, the EEG time series underwent normalization to ensure consistent scaling across different datasets. Additionally, artifacts and noise were removed using standard EEG preprocessing techniques.

2.3 Data Categorization

The EEG data was processed following the steps below:

1. **Data Loading:** The data was loaded from a CSV file containing EEG time series represented as lists of values.
2. **Calculation of Tsallis Entropy:** Tsallis entropy was calculated for each EEG time series using the formula above.
3. **Data Categorization:** The time series were categorized based on the calculated entropy, using thresholds to define categories of low, medium, and high entropy. Thresholds for categorizing low, medium, and high entropy were determined based on statistical analysis of the dataset's entropy distribution. The thresholds were set at the 33rd and 66th percentiles to divide the data into three approximately equal groups.

3 Results

After processing the data, we obtained three categories of entropy:

- **Low Entropy:** Time series with entropy below the low threshold.
- **Medium Entropy:** Time series with entropy between the low and high thresholds.

- **High Entropy:** Time series with entropy above the high threshold.

The data was saved in separate CSV files for each category, allowing for a more detailed analysis of the characteristics of the EEG time series based on the calculated entropy.

4 Discussion

The ability of Tsallis entropy to distinguish between levels of complexity in EEG signals has important implications for clinical and experimental research. High entropy patterns could be indicative of neurological disorders characterized by erratic brain activity, such as epilepsy or schizophrenia, whereas low entropy could be associated with more predictable states like deep sleep or anesthesia.

Statistical analysis revealed significant differences between the categories (p ¡ 0.05), suggesting that Tsallis entropy effectively discriminates between varying levels of brain activity complexity. The "High" entropy group consistently demonstrated greater signal variability, while the "Low" entropy group exhibited more stable, predictable patterns.

For example:

- The time series with entropy of 1.9515071355031128, classified as "High", indicated a more complex pattern that may reflect increased brain activity or variability.
- Time series with constant entropy of 1.9514928749927334 were categorized as "Low", suggesting more uniform and predictable patterns.
- Time series with values like [-0.0088481121211..., 0.90016471781772...] had entropies that fell within the "Low" range, indicating lower complexity.

These observations are consistent with the idea that Tsallis entropy can capture nuances in the complexity of EEG time series that are not evident with classical entropy measures.

5 Conclusion

This study demonstrates the effectiveness of Tsallis entropy in categorizing the complexity of EEG signals, providing deeper insights into brain activity. Future research could explore the application of this methodology to other neurological data or investigate how varying the q-parameter influences entropy calculations in different brain states. The approach also holds promise for enhancing diagnostic tools for neurological disorders through complexity analysis.

6 Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

7 References

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