Enhancing EEG-Based Imagined Speech Recognition Using Information Sets

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Introduction

Imagined speech is a form of speech wherein the individual mentally articulates words without any physical movement. In this work, we perform an Imagined speech classification task using **EEG signals**, with the intent being to decode the thoughts from EEG signals. We propose a novel approach to extract **rich spatio-temporal features** using Information set theory techniques to capture more information and improve classification. We improve over the **feature extraction** and **feature selection** parts by utilising information sets to extract effective features over spatial and temporal dimensions which better captures the information present in the imagined speech segment of the EEG data. The proposed approach is tested on the **KaraOne database**, obtaining average accuracies of 70% – 95% on five different binary phonological tasks, and trained using multiple independent **classifiers** including Hanman classifier, SVM, and Random Forest.

Potential applications include brain-computer interfaces (BCIs) for communication in military settings, assistive technologies for individuals with speech impairments due to various neuro-biological disorders such as **Alzheimer's** disease, **Parkinson's** disease, and amyotrophic lateral sclerosis (**ALS**) where there is an impairment in physical movement but not in cognitive function.

Keywords: Imagined speech classification, EEG signals, Spatio-temporal features, Information set theory, Machine learning.

Objectives

- Conduct a **classification task** utilizing the EEG Imagined speech dataset.
- Extract **rich spatio-temporal features** using Information set theory techniques to capture more information and improve classification.

Recording

Each trial consisted of four states:

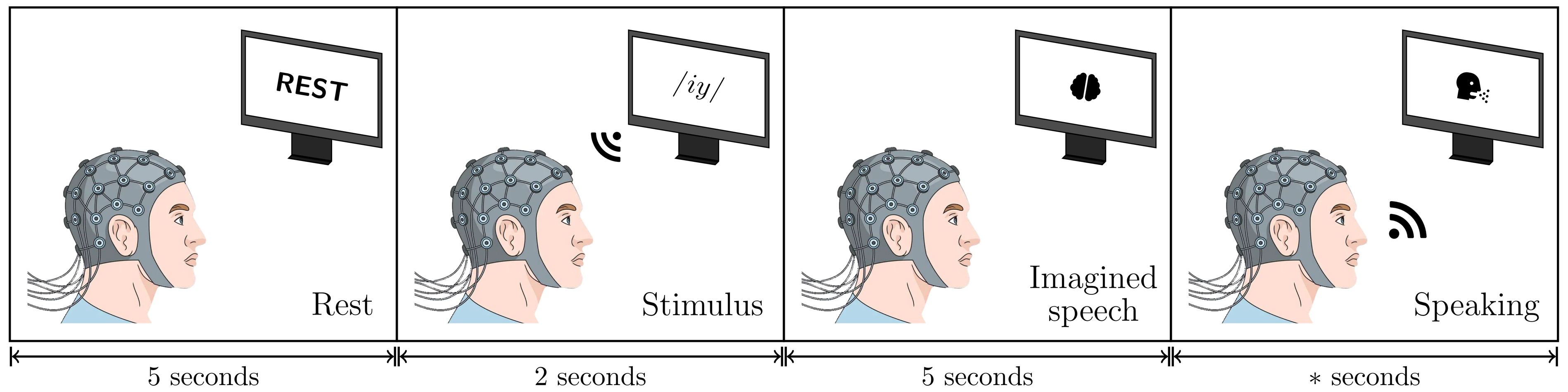
1. A 5-second **rest** state, where the participant was directed to relax and clear their mind of any thoughts.
2. A **stimulus** state, where the prompt text would appear on the screen and its associated audio file was played over the computer speakers. In this 2-second period, the participant also moved their articulators into position to begin pronouncing the prompt.
3. A 5-second **imagined** speech state, in which the participant imagined speaking the prompt in their minds without any movement.
4. A **speaking** state, in which the participant spoke the prompt aloud while the Kinect sensor recorded both the audio and facial features.

References

[1] Shunan Zhao and Frank Rudzicz. Classifying phonological categories in imagined and articulated speech. In *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 992–996, 2015.

[2] GitHub Repo: https://github.com/AshrithSagar/EEG-Imagined-speech-recognition

Dataset



KaraOne database [1] contains the data from **14 participants** (four female and eight male) over **three modalities**: EEG signals, face tracking, and audio signal acquired using a Microsoft Kinect (v.1.8) camera and a 64-channel Neuroscan Quick-cap, during imagined and vocalised phonemic and single-word prompts. It contains the data with a sampling frequency of 1000 Hz from 62 EEG channels. The cues consist of **seven phonemic/syllabic prompts** (/diy/, /iy/, /m/, /n/, /piy/, /tiy/, /uw/) and **four words** chosen from Kent's phonetically-similar pairs (gnaw, knew, pat, pot).

Proposed methodology

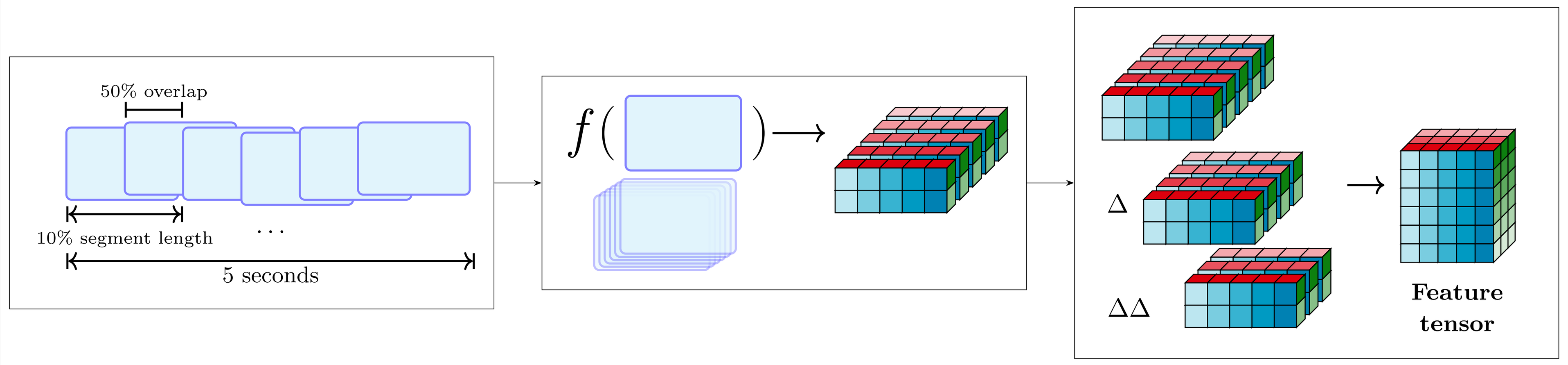


Figure 1: Preprocessing workflow: (a). Windowing (b). Feature extraction (c). Addition of delta & double delta features.

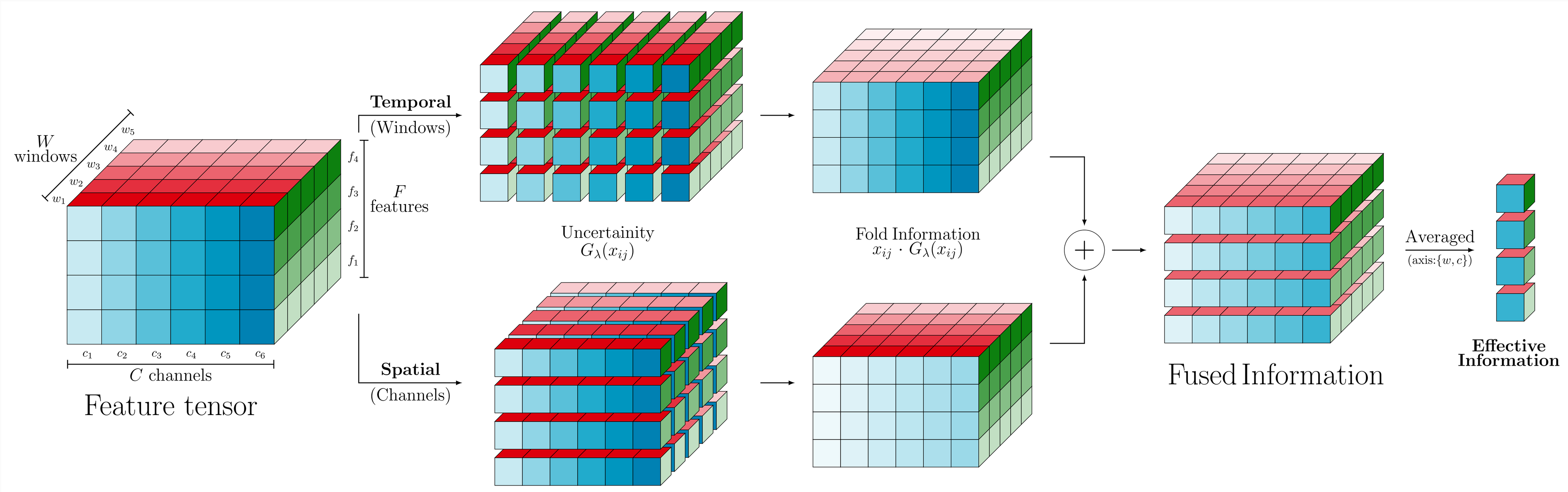


Figure 2: Extracting rich spatio-temporal features using Information set theory techniques.

In this study, we only focus on the 5-second **Imagined speech segment**. Data **preprocessing** was carried out using Bandpass filters, followed by **windowing** of the signals performed with a window size about 10% of the segment length, with 50% overlap between consecutive windows. This was followed by **feature extraction** and the addition of **delta and double delta features**, which are the differential features. The feature matrix is then transformed using **Information set theory** techniques by computing the two-fold information matrices using a **Gaussian membership function** across the temporal and spatial axes of the data separately. These were **fused**, followed by averaging along the temporal and spatial axes, giving the **effective feature vectors**, which form an effective representation. The effective feature vectors are then used to train multiple classifiers, including **Hanman classifier**, **SVM**, and **Random Forest**, and the performance of the features is evaluated.

Expected outcomes

- The proposed approach is expected to **improve the classification performance** of the EEG-based imagined speech recognition tasks.
- The rich spatio-temporal features extracted using Information set theory techniques are expected to offer **better differentiating power** and drastically **reduce the dataset size** used for training without sacrificing classification performance.
- The proposed approach is expected to address the issue of not being able to **effectively utilise all the information** present in the EEG signals, without sacrificing computational complexity of the feature space.

Conclusion

The rich spatio-temporal features extracted using the Information set theory techniques offer **better differentiating power** and **reduce dataset size** without sacrificing classification performance. They effectively utilise EEG signal information while **minimising computational complexity**. Creating precise and dependable imagined speech categorization models holds significant implications for both **human-computer interaction** and **cognitive neuroscience**. These models help us comprehend the intricate relationship between cognitive processes, neural activity, and external behavior, leading to more **user-friendly technology interfaces** and furthering our understanding of human cognition and brain function.

Future work could involve exploring **deep learning models** for the same problem, or with a **multi-class classification** setup, and comparing the results with the current implementation.

Call for collaborations

We are seeking collaborations with specialists working on **rehabilitation** and **assistive technologies**, specifically those interested to have applications in the field of **machine learning**, **deep learning** and **signal processing**. We would be extremely interested in collaborating with those interested in **data acquisition** from patients and **conducting clinical trials**, particularly those working with **EEG signals**.

If you are interested in collaborating with us, please feel free to contact us!

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