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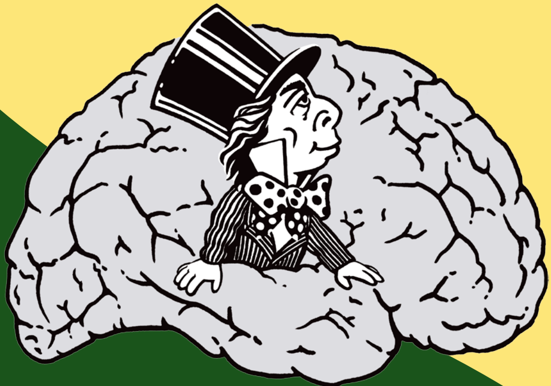

НОВЫЕ ИССЛЕДОВАНИЯ

МАТЕРИАЛЫ КОНФЕРЕНЦИИ 2023

Под ред. Е.В. Печенковой, М.В. Фаликман, А.Я. Койфман

УДК 159.9
ББК 88.25
К57

Когнитивная наука в Москве: новые исследования. Материалы конференции 21–22 июня 2023 г. Под ред. Е.В. Печенковой, М.В. Фаликман, А.Я. Койфман. – М.: ООО «Буки Веди», Московский институт психоанализа. 2023 г. — 604 стр.

ISBN 978-5-4465-3880-5

УДК 159.9
ББК 88.25

ISBN 978-5-4465-3880-5
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UNRAVELING COGNITIVE PROCESSES WITH A VAE-HMM APPROACH FOR IEEG ANALYSIS

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Abstract. This study proposes a novel method for analyzing intracranial electroencephalography (iEEG) data using a Variational Autoencoder Hidden Markov Model (VAE-HMM) with a domain-informed structure. Our approach allows for the joint modeling of neural sources of high gamma activity and their temporal dynamics. We aim to unmix neural sources, estimate their high gamma activity, and temporally cluster brain states, potentially leading to a deeper understanding of cognitive processes and their neuronal underpinnings. The proposed model integrates an encoder and a decoder for neural source power estimation and a Hidden Markov Model for temporal clustering. We demonstrate the effectiveness of our algorithm using a 5-minute data recording from a 20-channel ECoG grid during a picture naming test. The VAE-HMM method successfully identified underlying brain states associated with speech production and disentangled the contributions of different neural sources to the recorded iEEG signals. This approach offers a promising avenue for analyzing iEEG data and deciphering the dynamics of cognitive processes, with potential applications in various cognitive tasks, clinical settings, and other EEG rhythms.

Keywords: iEEG analysis, VAE-HMM, high gamma activity, temporal clustering, source modeling

The study was implemented in the framework of the Basic Research Program at the National Research University Higher School of Economics (HSE University) in 2023.

Introduction

Gaining insight into the dynamics of cognitive processes and their underlying neuronal sources is vital for expanding our understanding of brain function. Intracranial electroencephalography (iEEG) offers numerous advantages for studying cortical processes, such as high temporal and spatial resolution as well as reduced noise and artifact contamination. A prevalent analysis approach focuses on the augmentation of high gamma (70 – 150 Hz) power which is linked to various cognitive processes (Mercier et al., 2022).

The typical experimental paradigm for studying cognitive processes often involves averaging data across multiple experimental epochs or comparing it between experimental and baseline blocks. This allows researchers to assess the modulation of high gamma power in relation to specific cognitive tasks or states. Despite the high signal-to-noise ratio observed in high gamma augmentation, analyzing data recorded during natural tasks, such as continuous speech, creates challenges including the temporal variability in brain high gamma augmentation.

Approaches like source power correlation (SPoC; Dähne et al., 2014) utilize target variables to estimate neural sources. However, in the context of speech and language research, observable target variables, such as the envelope of the produced speech, may provide limited information about the underlying processes. Therefore, alternative approaches are needed to better capture the complex dynamics of speech and language processing at the neural level.

In this study, we propose a novel method for analyzing iEEG data using a Variational Autoencoder Hidden Markov Model (VAE-HMM) with a domain-informed structure. This approach allows us to jointly model the neural sources of high gamma activity and their temporal dynamics. VAE-HMM is a Bayesian network that is adept at modeling temporal dynamics in a probabilistic manner (Ebbers et al., 2017) making it readily applicable to neuroscience research.

Through the training of the Variational Autoencoder, the spatial filter is learned to effectively separate the neural sources, and then it approximates the amplitude envelopes of the sources by taking an absolute value. This approach resembles the common pipeline for iEEG analysis — applying spatial filter to the bandlimited signal (typically common average reference) and gating amplitude envelope by taking an absolute value of the analytic signal provided by Hilbert transform.

The Hidden Markov Model (HMM) is then employed to temporally cluster the approximate envelopes based on their amplitude profiles and temporal continuity. During the training process, prior information can be provided to the HMM, allowing for the association of specific patterns, such as resting periods or eye movement activity, with particular clusters. This integration of prior knowledge within the probabilistic structure of the VAE-HMM enables a principled and domain-grounded approach to incorporate observable information.

By employing the VAE-HMM method, our aim is to unmix neural sources, estimate their high gamma activity profiles, and temporally cluster brain states which would allow us to decouple the observed mixture of neuronal activations to gain a deeper understanding of the complex dynamics of cognitive processes and their neuronal underpinnings (Forseth, 2021).

Method

The proposed model integrates an encoder and a decoder for the estimation of the amplitude in the high-gamma band of the neural sources as well as a HMM for temporal clustering of the brain states (Figure 1). The encoder serves as an inverse model that disentangles the data from iEEG sensors into distinct neural sources while estimating the amplitude of high gamma activity from the narrow-band filtered data. Given the known signal components from the encoder, the decoder carries out a linear transformation eliminating the need for sampling during

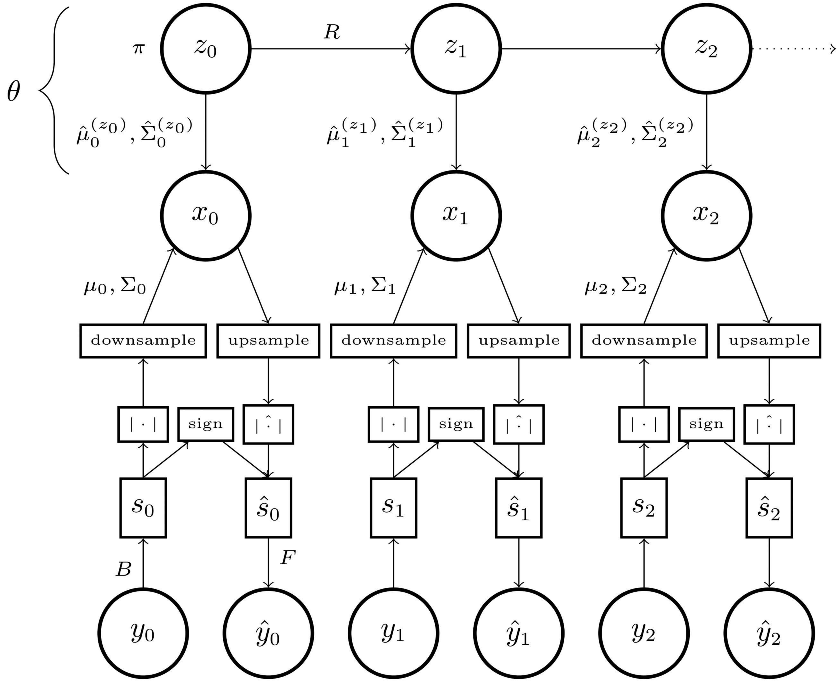

Figure 1. Schematic representation of the VAE-HMM. Variables "y" represent iEEG in high-gamma frequency band, variables "x" represent slowly changing source activity (closely related to the high-gamma envelope), and variables "z" represent the brain states

VAE training. The VAE and HMM components are trained alternately; the HMM provides the posterior for the VAE, while the VAE generates dynamic variables for the HMM. This alternating training process results in an increase of the Evidence Lower Bound (Bishop, Nasrabad, 2006):

$$\log p(\mathbf{y} \mid F, \theta) \geq \underbrace{\mathbb{E}_{q(\mathbf{x}|B)} \{\log p(\mathbf{y} \mid \mathbf{x}; F)\}}_{\text{VAE Reconstruction}} - \underbrace{\mathbb{E}_{q(\mathbf{z})} \{D_{KL}[q(\mathbf{x} \mid B) \parallel p(\mathbf{x} \mid \mathbf{z}; \theta)]\}}_{\text{VAE-HMM Interaction}} - \underbrace{D_{KL}[q(\mathbf{z}) \parallel \log p(\mathbf{z} \mid \theta)]}_{\text{HMM Transition}}.$$

Throughout the iterations, maximum likelihood estimates (MLE) of the HMM parameters θ have closed-form solutions, while the VAE optimization is performed using a stochastic gradient-based method.

To demonstrate the performance of the proposed algorithm, we utilized a five-minute recording from a 20-channel ECoG grid during a picture naming test. The ECoG grid was positioned on the middle and superior frontal gyri while the patient was awake, undergoing surgery for epilepsy treatment. Out of the 20 electrodes, 15 were functioning properly. The ECoG was recorded at a sampling rate of 4096 Hz, concurrently with the patient's speech production during

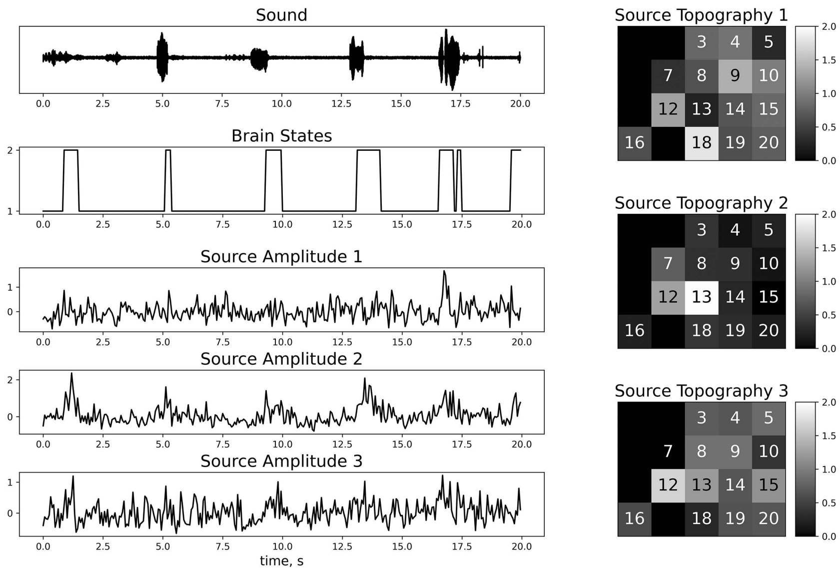

Figure 2. Visualization of the neural sources, states, and speech during the picture naming task. The iEEG data in the high-gamma frequency band is initially transformed into three distinct sources, each with its own topography on the ECoG grid and time-varying amplitude, and subsequently into two temporal clusters

the test. For our parameters, we opted for three sources and two states, and the estimated source amplitude was downsampled to a resolution of 16 Hz.

Results

Our VAE-HMM method successfully identified underlying brain states associated with speech production during the picture naming test, as evidenced by the consistent correspondence between the inferred states and speech production (Figure 2).

The topographies of the neural sources visualized using the absolute values of the forward model's weights revealed distinct spatial patterns. These patterns provided insights into the spatial distribution of the neuronal sources contributing to high gamma activity during the task.

Discussion and Conclusions

The VAE-HMM method presented in this study provides a promising avenue for analyzing the iEEG data and deciphering the dynamics of cognitive processes. Future research could extend the application of the VAE-HMM to various cognitive tasks, examine its potential in clinical settings, explore its applicability to other EEG rhythms, and improve its performance by incorporating a more sophisticated model structure. This could include the use of an autoregressive HMM and the integration of temporal information about states, such as resting periods or speech periods, to refine state distribution and enhance the model's performance.

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РАСШИФРОВКА КОГНИТИВНЫХ ПРОЦЕССОВ С ПОМОЩЬЮ МЕТОДА VAE-HMM ДЛЯ АНАЛИЗА ИНТРАКРАНИАЛЬНОЙ ЭЭГ

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Аннотация. В данном исследовании предлагается новый метод анализа данных интракраниальной электроэнцефалографии (иЭЭГ) с использованием вариационного автоэнкодера скрытой марковской модели (VAE-HMM). Наш подход позволяет одновременно моделировать нейронные источники высокочастотной гамма-активности и их временную динамику, что может привести к более глубокому пониманию когнитивных процессов и их нейронных основ. Предложенная модель интегрирует кодировщик и декодер для оценки мощности нейронных источников и скрытую марковскую модель для временной кластеризации. Мы демонстрируем эффективность нашего алгоритма на примере 5-минутной записи данных с 20-канальной сетки ЭКоГ во время теста на называние картинок. Метод VAE-HMM успешно определил базовые состояния мозга, связанные с порождением речи, и разграничил вклад различных нейронных источников в записанные сигналы иЭЭГ. Этот подход является перспективным для анализа данных иЭЭГ и расшифровки динамики когнитивных процессов, он может применяться в клинической практике, для анализа других ритмов ЭЭГ и различных когнитивных задач.

Ключевые слова: анализ иЭЭГ, VAE-HMM, высокочастотная гамма-активность, временная кластеризация, моделирование источников

Исследование осуществлено в рамках Программы фундаментальных исследований НИУ ВШЭ в 2023 году.