Coupled Hidden Markov Model for Electrocorticographic Signal Classification

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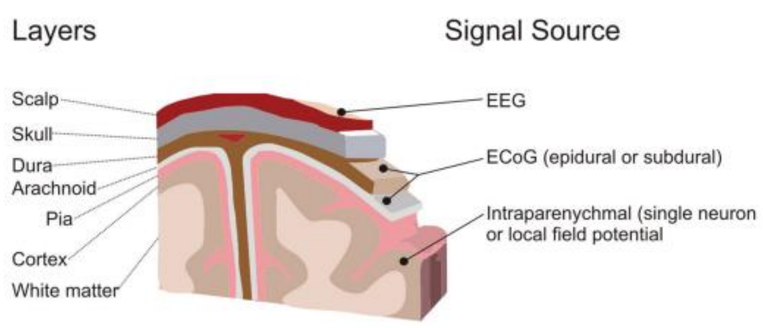
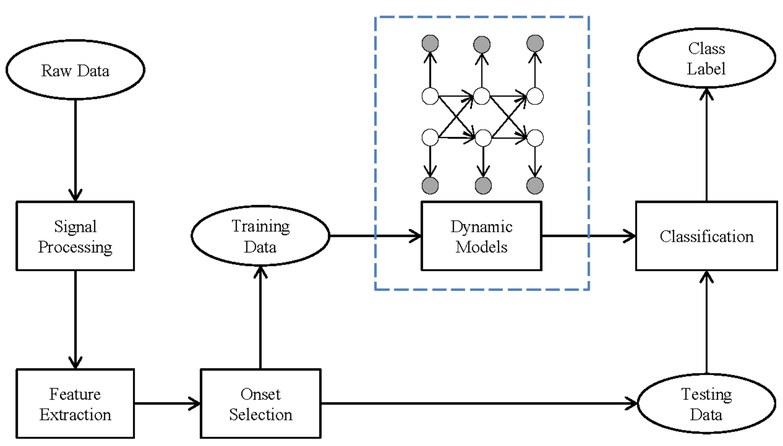
Introduction

- **Electrocorticographic (ECoG)**: One modality of brain signals obtained by invasive surgery.
- **Quality**: Fine resolution in both space and time with substantially high signal noise ratio compare to EEG.
- **ECoG signal classification**: Different dynamic patterns in response to different exterior stimulus. Important for brain computer interface (BCI) application.



Objective

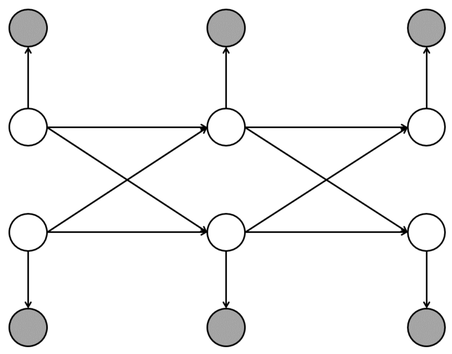
Model the spatial and temporal dynamics of multi-channel ECoG signals and classify the signals recorded under different conditions of hand motion task.



Methods & Models

A. Model Description

- **Coupled Hidden Markov Model (CHMM)** is applied to capture the ECoG signal spatial and temporal dynamics between different channels.
- Aggregate multiple HMMs together by allowing transition between hidden nodes from different HMMs.
- CHMM is more expressive because it allows different number of states to be applied for each individual HMM.



Shaded nodes are observed.

Unshaded nodes are hidden.

B. Parameterization

Joint probability distribution of CHMM:

$$P(\mathbf{Y},\mathbf{X}) = \prod_{c=1}^{C} P(X_c^1) \prod_{t=2}^{T} P(X_c^t|\mathbf{X}^{t-1}) \prod_{t=1}^{T} P(Y_c^t|X_c^t)$$

where $\mathbf{Y_c} = \{Y_c^1, \dots, Y_c^T\}$, $\mathbf{X}_c = \{X_c^1, \dots, X_c^T\}$, $c = 1, \dots, C$ are continuous observed variables and discrete latent variables respectively in the cth HMM with C channels in total.

a) Initial distribution

$$P(X_c^1 = n_c) = \pi_{n_c}, 1 \le n_c \le N_c$$

where N_c is the number of hidden states of cth HMM and $\sum_{n_c=1}^{N_c} \pi_{n_c} = 1, \pi_{n_c} \ge 0$.

b) Transition distribution

$$P\left(X_k^{t+1} = n_k \middle| X_1^t = n_1, \dots, X_C^t = n_C\right) = a_{n_1 \dots n_C}^{n_k}$$

where $\sum_{n_k=1}^{N_k} a_{n_1 \dots n_C}^{n_k} = 1, a_{n_1 \dots n_C}^{n_k} \ge 0$.

c) Emission distribution

$$P(Y_c^t|X_c^t = n_c) = N(\mu_{n_c}, \Lambda_{n_c})$$

where $1 \le n_c \le N_c, \mu_{n_c}$ and Λ_{n_c} are mean and covariance matrix.

C. Computation

- **Parameters learning:**

Expectation maximization (EM) algorithm.

- **Probability inference:**

Forward-backward algorithm.

- **Training:** Learn CHMMs for each one of eight possible directions of hand movement.
- **Testing:** The model which produces highest probability likelihood of observations decides the class label.

$$\hat{k} = \arg\max_k P(\mathbf{Y}|\theta_k)$$

Experiment

A. Data collection

- **Human subject joystick control task:** Hold joystick to move cursor on the screen to hit a virtual target located in one of eight possible locations.

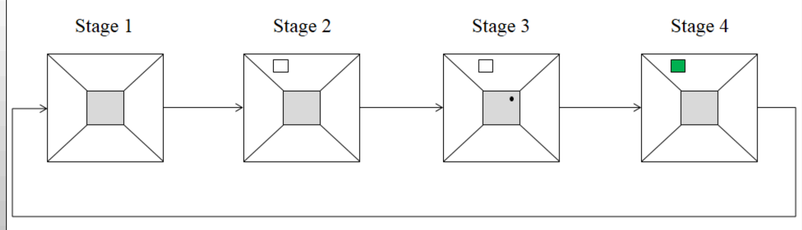
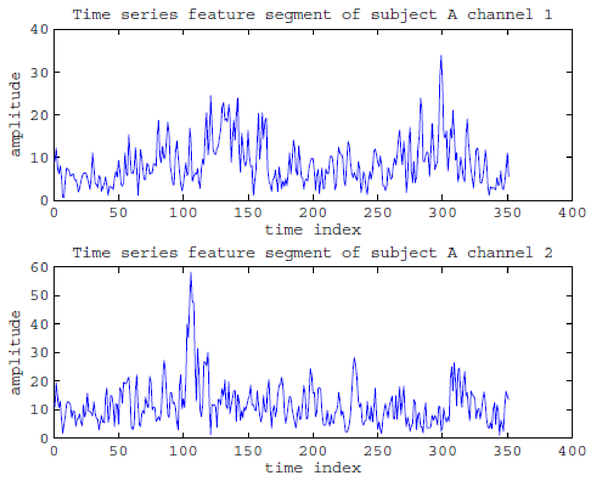


TABLE I. SUBJECTS PROFILE AND NUMBER OF SEGMENTED SEQUENCES USED IN TRAINING AND TESTING

Subject	Gender	Age	Training Sequences	Testing Sequences
A	Female	29	206	203
B	Male	25	93	91
C	Male	25	186	180
D	Female	49	95	89

B. Signal processing and feature extraction

- **Original ECoG signal:** Sampled at 1200Hz for each channel.
- **Processing**
  - Exclude significant line noise channels.
  - Common average filtering all channels.
  - Notch filtering harmonics of line noise.
  - Spectrum filter followed by Hilbert transform to obtain amplitude envelope of high gamma band of range 70-170 Hz.
  - Down-sample to 200 Hz.
- **Channel selection:** Two channels that cover motor cortex area.
- **Temporal alignment:** Onset of stimulus or joystick motion.



Result & Discussion

TABLE II. CLASSIFICATION ACCURACY ON TEST SET FOR EACH SUBJECT

Subject	A		B		C		D	
Onset	Stimulus	Joystick	Stimulus	Joystick	Stimulus	Joystick	Stimulus	Joystick
CHMM	0.1872	**0.2167**	**0.2308**	0.1868	**0.2111**	**0.2278**	**0.2135**	**0.2360**
HMM	**0.1921**	0.1872	0.1978	**0.1978**	0.1778	0.2111	0.1461	0.1685
AR	0.1478	0.1379	0.1099	0.1209	0.1667	0.1500	0.2022	**0.2360**

- **CHMM vs. HMM :**
- Subject A, CHMM improves classification rate by 16% with joystick onset alignment.
- Subject B, CHMM improves classification rate by 17% with stimulus onset alignment.
- Subject C and D, CHMM is better on both alignment with average improvement rate 14% and 43% respectively.
- **CHMM vs. Autoregressive model (AR) :**

Significant improvement in all cases.

Conclusion & Future work

- We employed CHMM on multi-channel ECoG signals to capture the temporal interactions among brain signals during motor task. Comparing to HMM and AR model, CHMM is more expressive with overall better classification accuracy.
- For future work, we plan to include more channels and frequency bands as features and design models robust to the temporal variation between different trials.