

# Neuromatch Pod-Raclette Group 2

Our development after NMA (add yours here if you come back!):

## Info

1. Mentor: Huihui Zhang
2. Topic:
  - a. dataset1 = faces/houses  
Votes: 1
  - b. dataset2 = fingerflex  
Votes:
  - c. dataset3 = joystick track  
Votes:
  - d. dataset4 = Memory back  
Votes:
  - e. dataset5 = motor imagery  
Votes: 4
3. Work:
  - a. Experiment Design Farhad
  - b. Fig1 Huayu
  - c. Fig2 Xianhui
  - d. Fig3 Hanif
  - e. Fig4 Shaurya
  - f. Fig5 Ramy
  - g. Result Farhad
4. Mentor Meeting Time: GMT+8 Wednesday 10:00am-11:00am

Xianhui He (何贤辉)

[http://mailto:xhhe.psy@gmail.com](mailto:xhhe.psy@gmail.com)

Ramy Ali

[http://mailto:s-ramy.ali@zewailcity.edu.eg](mailto:s-ramy.ali@zewailcity.edu.eg)

Nan Chen

[http://mailto:chennan5353@gmail.com](mailto:chennan5353@gmail.com)

Huayu Wang

[http://mailto:why123jj@126.com](mailto:why123jj@126.com)

Shaurya Goyal

[http://mailto:shauryagoyal789@gmail.com](mailto:shauryagoyal789@gmail.com)

Hanif Rachmadani

[http://mailto:hanif.rsiwanto@gmail.com](mailto:hanif.rsiwanto@gmail.com)

Farhad Tabasi

[http://mailto:tabasif@gmail.com](mailto:tabasif@gmail.com)

## 7.13 Report

**Figure 2:**

- A. the role of High frequency band and Low frequency band in imagery may be different
  - imagery and actual movement share more similar characteristics in low frequency band than in high frequency band
- B. detailed information about the overlap results in each participant
  - similar pattern to the group mean (see figure 1)

**Figure 3:**

An experiment was done with 4 subjects in an imagery-based learning task to control a cursor on screen using particular electrodes from previous movement task experiment

Figure 3A

- Electrode-Frequency combination of **gold electrode, 79-95Hz, around primary tongue cortex**
- Measured power **P(t)** then used control a cursor (**its velocity**) with simple linear equation, evry 40ms from P(t) during the previous 280ms in respect to mean power **P<sub>o</sub>**
- Imagery done by “**imagining**” saying the word **move** to move the cursor as **active target**, and just **rest (doing nothing)** as **passive target**

Figure 3B

- During 4 consecutive run, red dot indicates active target, blue dot passive target, green line indicates **P<sub>o</sub>**, mean power across passive/active trials
- Accuracy **increases for every run** with the **highest** one at **run 4**
  - Of particular note, subject reported ceased to perform imagery, and “just thought about moving the cursor up and down to move”

Figure 3C

- Activations of LFB & HFB across all electrodes were shown, with **increasing activation in the corresponding area (tongue cortex) & frequency (HFB) throughout the trials with run 4 being the highest**

### Result

1. the spatial distribution of local neuronal population activity during **motor imagery mimics**

the spatial distribution of activity during **actual motor movement**.

2. The role of **primary motor areas** in movement imagery was revealed by significant imagery-induced cortical surface activity at electrode sites where electrocortical stimulation produced movement.

The magnitude of imagery-induced cortical activity was ~**25%** that of actual movement.

When this same imagery was used to control a cursor in a simple feedback task, we found an **augmentation** of spatially congruent cortical activity, even **beyond** that found during movement.

### 3. spatial distribution

	<b>overt movement and imagery (overlap?)</b>	<b>between movement types (overlap?)</b>
LFB (Low frequency band)	YES	YES
HFB (High frequency band)	YES	NO

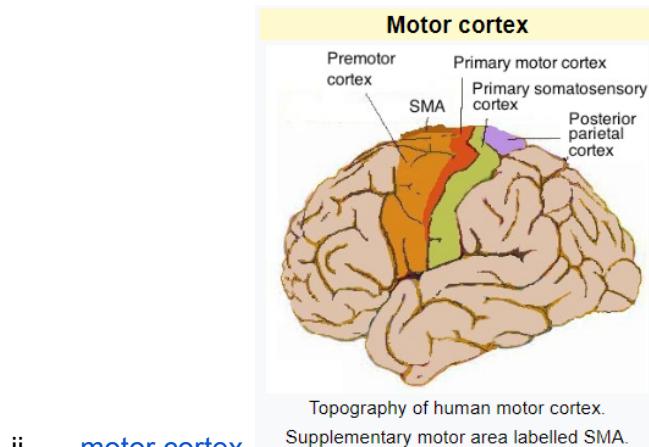
## Meeting Note

1. Xianhui: considering the functional differences of different frequency bands, we can classify the motor and imagery in one frequency band but classify the motor types (hand and tongue) in other frequency band
2. Hanif: The Dataset contains 3 subdataset, should we use all data or can we just use some of it? (update: only 2 subdataset)
3. Xianhui: do you mean we can examine the representation of motor types/motor-imagery is dynamic or stable by using the raw signal

## 7.14 Exploration

Notes:

- Huayu
- Xianhui
  - a. individual differences of channel locations
    - for i in range(7):  
    print(alldat[i][0]['gyrus'])
  - i. we should determine our ROI (region of interests), like IFG, STL...



- Nanchen:  
<https://www.sciencedirect.com/science/article/pii/S2590005619300037>(review)
- Hanif
- Ramy
- Farhad

## Questions

```
# high-pass filter above 50 Hz
b, a = signal.butter(3, [50], btype='high', fs=1000)
V = signal.filtfilt(b, a, V, 0)

# compute smooth envelope of this signal = approx power
V = np.abs(V)**2
b, a = signal.butter(3, [10], btype='low', fs=1000)
V = signal.filtfilt(b, a, V, 0)

# normalize each channel so its mean power is 1
V = V/V.mean(0)
```

(huayu)What is this filtfilt function doing to the voltage signal?

Xianhui: I think it keeps the signal in certain bands (10Hz-50Hz), but throw other bands (<10Hz or >50Hz). But typically people often keeps the signal within 1Hz-200Hz in Ecog dataset. ok thx!

Applying the filter iirc (it's a butterworth 3rd order high-pass 50hz) why they do it twice idk (H)  
I got it! But I have the same question regarding the second filter because they used lowpass?

Ah yess, missed that part, yeah the second is a low pass filter, i think it's for envelope calculation (kinda hazy about that part, envelope's mostly used in emg iirc)  
got it!

btw they absit to remove negative value and then smoothed it out with the envelope filter (making upper envelope)

i think they first abs the signal to get the amplitude, and then squared it to get the power?  
oops, they did not calculate the power, they calculate the envelop.

i think they did calculate approx power (i mean  $P = V^2/R$  so power is proportional to squared voltage right), then detect its upper envelope with filter (not sure about envelope detection overall tho, just understands some)

got it, I mix the two. the exact power can only be obtained by the time-frequency analysis

here if we didnt use the second filter (the envelope stuff one), just the approx power  
 $\text{abs}(v)^{**2}$

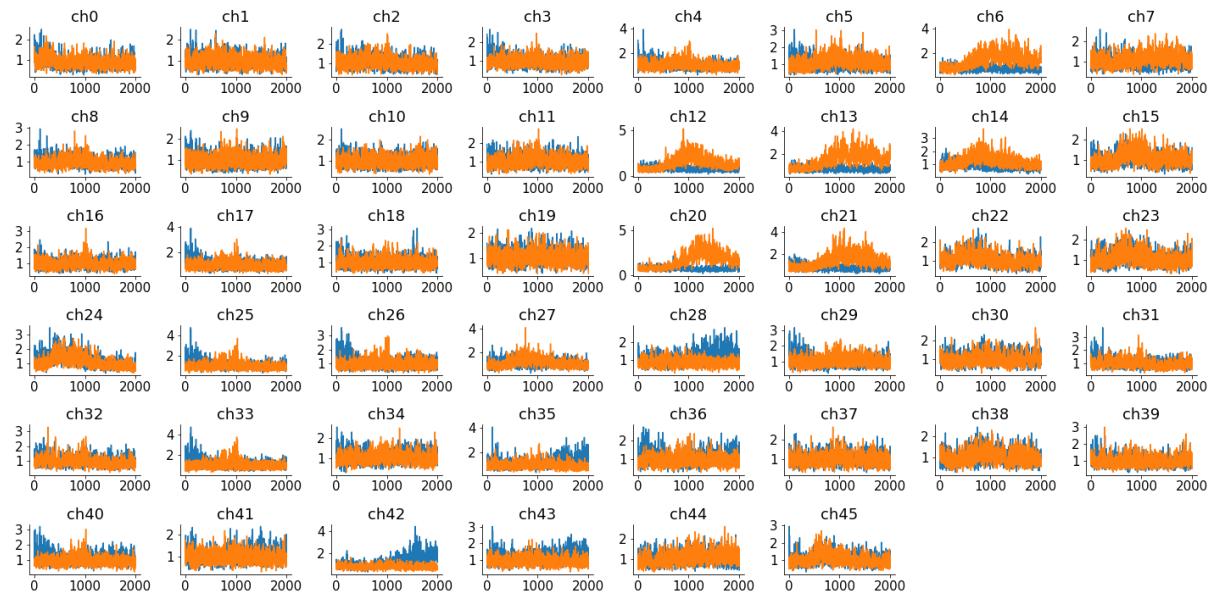
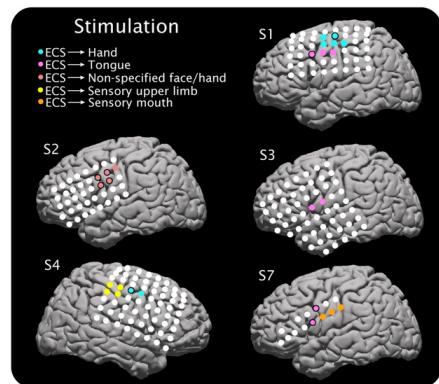


Table 1. channel number of each region

	SFG	MFG	Precentral Gyrus	Postcentral Gyrus	IPL	STG	MTL	ITL	others ...	
sub0	3	16	11	7	3	1	0	0		
sub1	2	17	9	4	0	9	9	0		
sub2	0	1	7	5	4	11	12	0		
sub3	3	12	11	6	10	0	0	4		
sub4	1	14	7	3	0	13	10	0		
sub5	5	17	14	8	5	6	0	0		
sub6	0	5	7	9	8	13	12	2		
	14	82	66	42	30	53	43	6		

there are so many regions they recorded, anyone has an idea about which regions should be used for our project?

- if we want to train a classifier, we may ensure each subject has the same number of samples/inputs, right?
- nevermind, hmmm is the data big enough if we want to use only one subject?
- seems like the paper didn't elaborate much regarding electrode locations on subject
- nevermind they did on supporting info:
- We can try to stick with S1 first if we want to (or try explore other subject)
  - yeah, that's a good idea



## Sensorimotor area as our ROI

-which electrodes corresponds to that area? -> Precentral Gyrus and Postcentral Gyrus

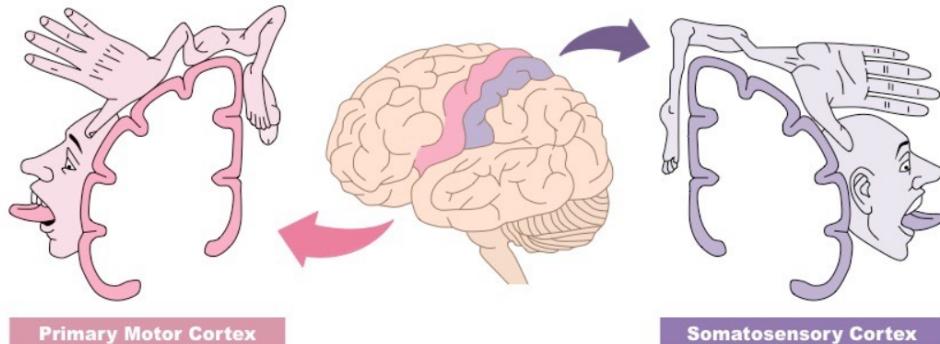
Tactile perception (touch) and gross physical movements are coordinated by the sensorimotor areas of the brain

- The primary motor cortex is located in the precentral gyrus (frontal lobe) and handles motor signals
- The somatosensory cortex is located in the postcentral gyrus (parietal lobe) and handles tactile sensory signals

These two regions each form a *cortical homunculus* – a neurological map of the anatomical divisions of the body

- Parts of this representation of the human body are disproportionately large as these regions are highly innervated
- The hands, tongue and lips are very large as these appendages require more nervous control (e.g. for speech)
- Areas with less innervation (e.g. torso) have less of the cortex dedicated to their functioning and appear small

#### Cortical Homunculus of the Sensorimotor Areas



**things to be done:** we need to know the index of the two areas in our dataset

- Should we check manually via graph?
- I am trying to get it (you can find my code in next page)

**here's mine (assuming dat[subject][trial]['gyrus'] is ordered by electrodes from 1-4x):**

```
for subject_index, subject in enumerate(alldat):  
    electrode_indexes_precentral = []  
    electrode_indexes_postcentral = []  
    for gyrus_index, gyrus in enumerate(subject[0]['gyrus']):  
        if gyrus == 'Precentral Gyrus':  
            electrode_indexes_precentral.append(gyrus_index)  
        elif gyrus == 'Postcentral Gyrus':  
            electrode_indexes_postcentral.append(gyrus_index)  
  
    print("""  
        Subject {}:\n        \\\n        Precentral Gyrus: {}\n        Postcentral Gyrus: {}\n    """.  
        format(subject_index,  
              electrode_indexes_precentral,  
              electrode_indexes_postcentral  
        ))
```

**results:**

**Subject 0:**

Precentral Gyrus: [5, 6, 7, 12, 20, 27, 28, 35, 36, 41, 42]

Postcentral Gyrus: [13, 14, 21, 29, 37, 43, 44]

**Subject 1:**

Precentral Gyrus: [7, 14, 15, 21, 22, 29, 30, 31, 37]

Postcentral Gyrus: [23, 38, 39, 47]

**Subject 2:**

Precentral Gyrus: [25, 26, 35, 36, 43, 44, 45]

Postcentral Gyrus: [27, 28, 29, 37, 46]

**Subject 3:**

Precentral Gyrus: [4, 5, 11, 12, 19, 20, 28, 35, 36, 42, 43]

Postcentral Gyrus: [3, 18, 26, 27, 34, 41]

**Subject 4:**

Precentral Gyrus: [7, 14, 21, 22, 23, 28, 29]

Postcentral Gyrus: [15, 30, 31]

**Subject 5:**

Precentral Gyrus: [0, 1, 8, 9, 10, 18, 26, 27, 34, 35, 43, 44, 52, 53]

Postcentral Gyrus: [16, 17, 24, 25, 33, 42, 50, 51]

**Subject 6:**

Precentral Gyrus: [34, 42, 43, 44, 51, 52, 60]

Postcentral Gyrus: [27, 28, 35, 36, 45, 53, 61, 62, 63]

## Ideas So Far (add yours here!) :

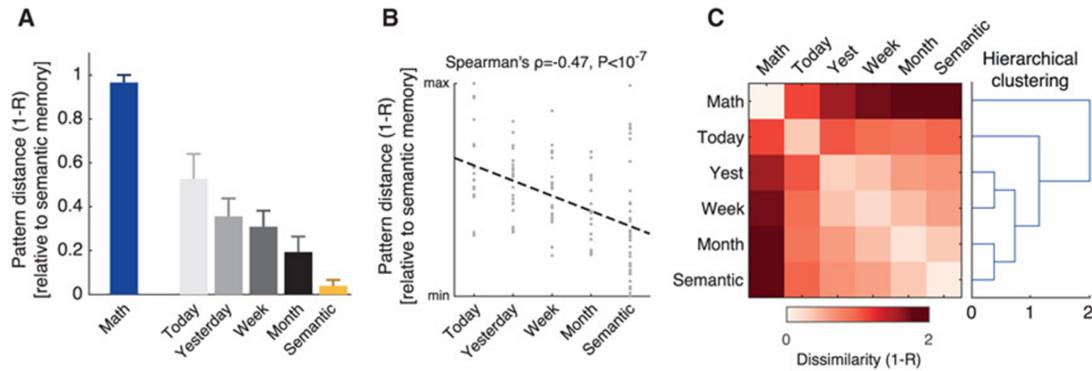
1. **Simple classifier model to differentiate hand-tongue signal** (train it using the active movement test (cross-validation, etc) and then test it for real with the imagery data, or maybe we can combine the data or something? i'm not that good with data wrangling :P -Hanif
  - my idea is like: train and test a classifier in real movement to make sure the classifier can decode movement types information, and then generalize (test) it to imagery data to see whether the classifier can still decode movement types.
  - if the generalization is good, we can conclude that the movement types representation in imagery is quite similar to the representation in real movement
  - by the way, the results of the generalization may depend on the types of signal (raw signal/ signal of low frequency band/ signal of high frequency band). It may be likely that the generalization is only good for certain type of signal, which may suggest the important role of this signal
  - I am not sure if we can combine the data, but we can surely have a try if we have a interesting question which requires us to do that :))
  - Wow, that's quite elaborate! interesting idea Xianhui, i think we can come up with some kind of a question!, That's one idea, anyone got more?

(related method review: <https://www.sciencedirect.com/science/article/pii/S2590005619300037>)

2. **Pattern similarity** (calculate the similarity matrix among the four conditions)

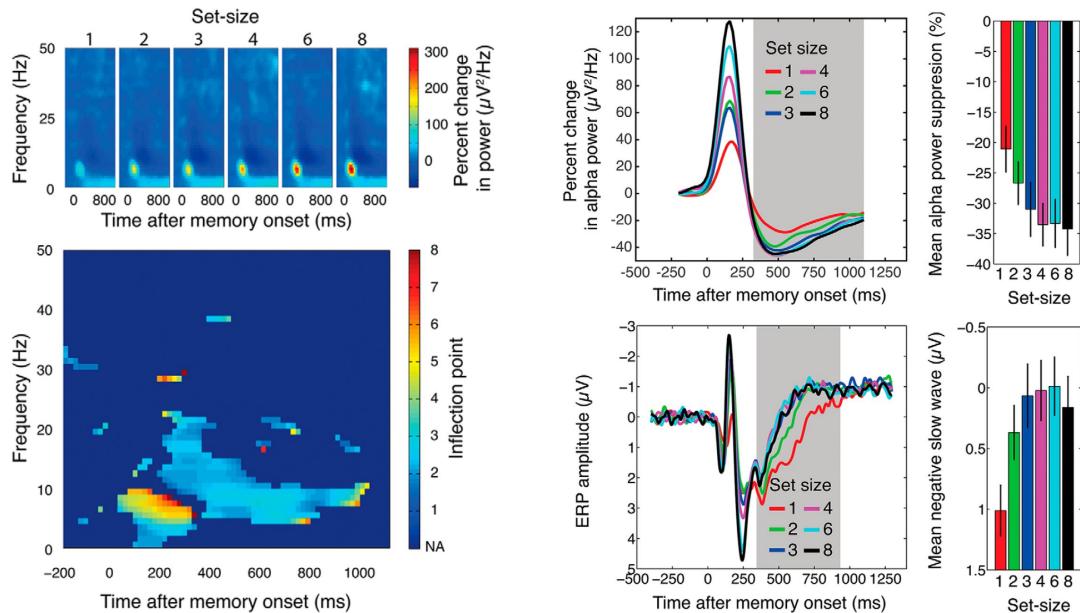
	hand (actual)	tongue (actual)	hand (imagery)	tongue (imagery)
hand (actual)	1			
tongue (actual)	xxx	1		
hand (imagery)	xxx	xxx	1	
tongue (imagery)	xxx	xxx	xxx	1

reference (<https://www.sciencedirect.com/science/article/pii/S089662732100461X>)



3. (WIP) ERP analysis of the difference between motor and imagery: i.e., how activation in different frequency bands and brain regions evolving over time differ between motor and imagery

I guess you mean time frequency analysis instead of ERP analysis. ERP used the raw voltage signal, while the time frequency analysis used the power/activation in different frequency bands. But both analyses are worth doing!



Fukuda, K., Mance, I., & Vogel, E. K. (2015). a Power Modulation and Event-Related Slow Wave Provide Dissociable Correlates of Visual Working Memory. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, 35(41), 14009–14016.

^looks kinda fun, got an idea what kind of hypothesis can be made?

I want to look at the activation sequence of different brain areas given different tasks (motor/imagery, hand/tongue). Perhaps imagery and motor activates the same brain areas in different order? But if it's all the same, it'll become very boring.  
interesting! I think we can do this as the first step, then try some further analyses.

^worth a try

True! We should do some data-wrangling.

currently messing around with MNE using the dataset (still learning the MNE library, still sucked at it)

4 - We can compare the activity between simple vocalization activity (in beta and gamma range) over motor cortex and other motor-related activities at the same regions. Then, we can use a classifier for their different.

can anyone try get the vocalization/speech dataset? idk where to get it

(everyone has one choice)

idea 1

- votes:

idea 2

- votes:

idea 3

- votes:

idea 4

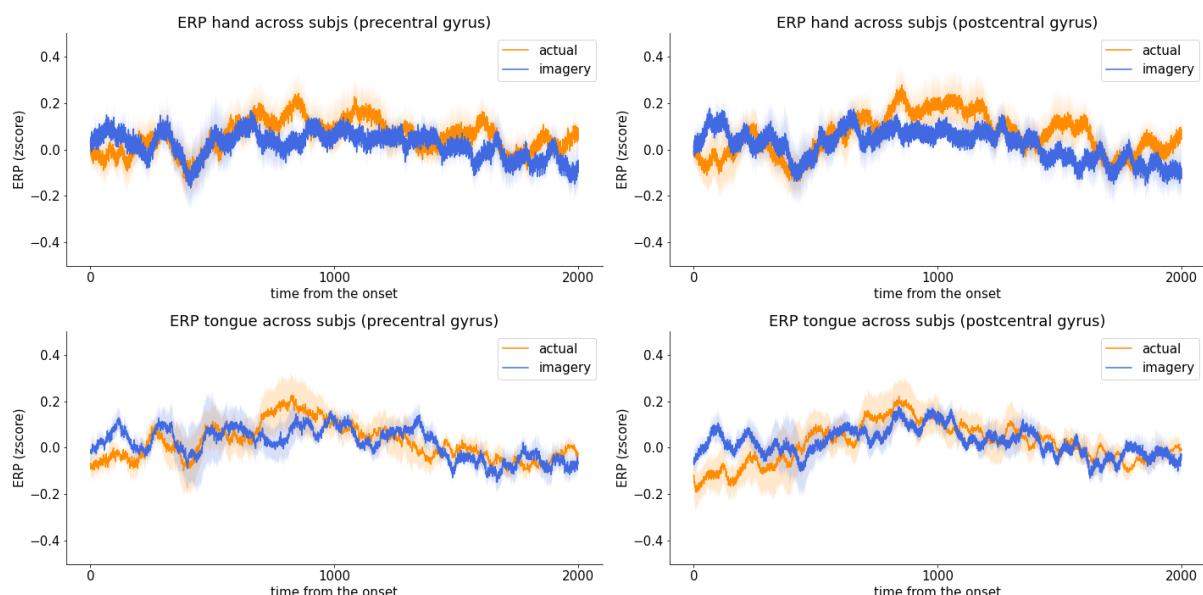
- votes:

Notes\_07.15

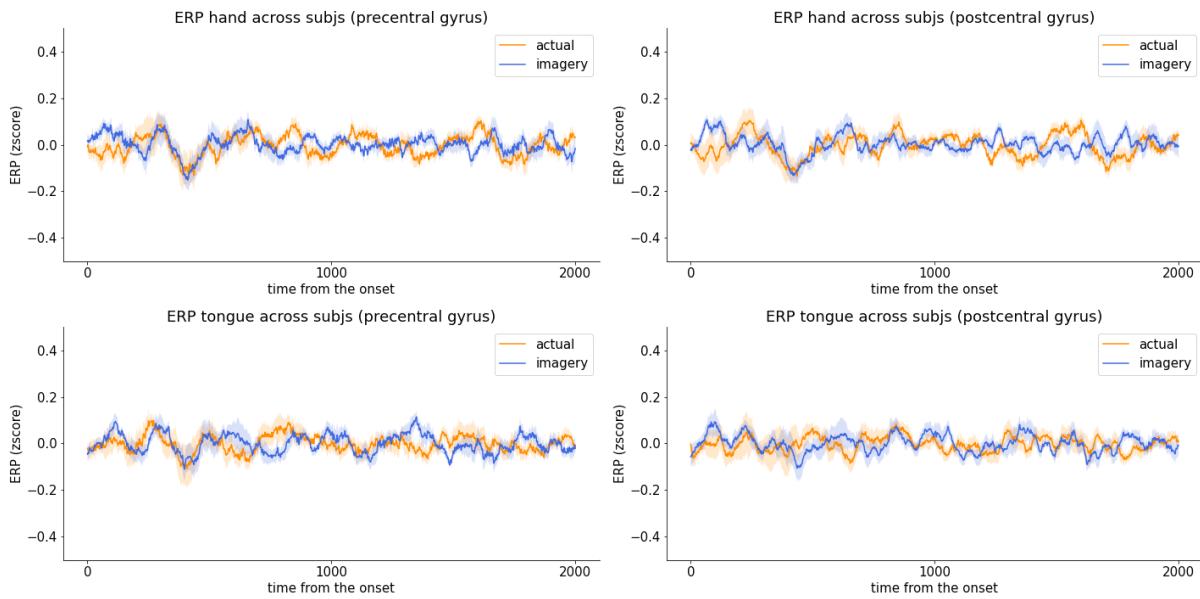
<https://mne.tools/stable/index.html> (mne toolbox)

## 7.18 Exploration

ERP



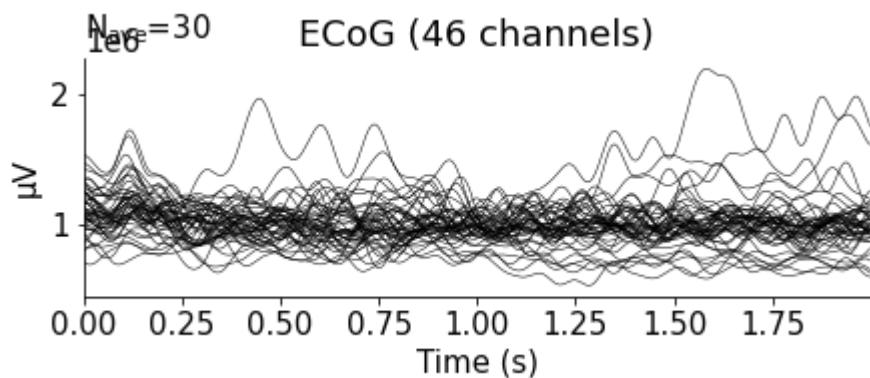
ERP within [1, 200Hz]



work:

- Literature review: Huayu & Nan
  - the differences in the neural correlates (ERP/frequency signals/function connectivity/activation/power/phase etc) between actual movement and imagery movement
  - how to quantify the differences of activation sequence?
  - DCM obtain the causal relationship between two areas
- Data analysis pipeline: Xianhui & Hanif & Ramy
  - how to do time-frequency analysis using MNE (Hanif & Ramy)
  - Ok, learning MNE now
  - Btw, are we fixed on using this dataset? Ok
  - how to do classifier using pytorch (Xianhui)

discuss at 10 am UTC + 8 for an hour (Tuesday) Done!



Finally managed to load the dataset to MNE (using its format)  
 (above is the average().plot(), all channels)

fantastic! I wonder whether we can do time frequency analysis now, because I want to discuss the results with our mentor

i'll try to do it today, should be easy (probably, hopefully)

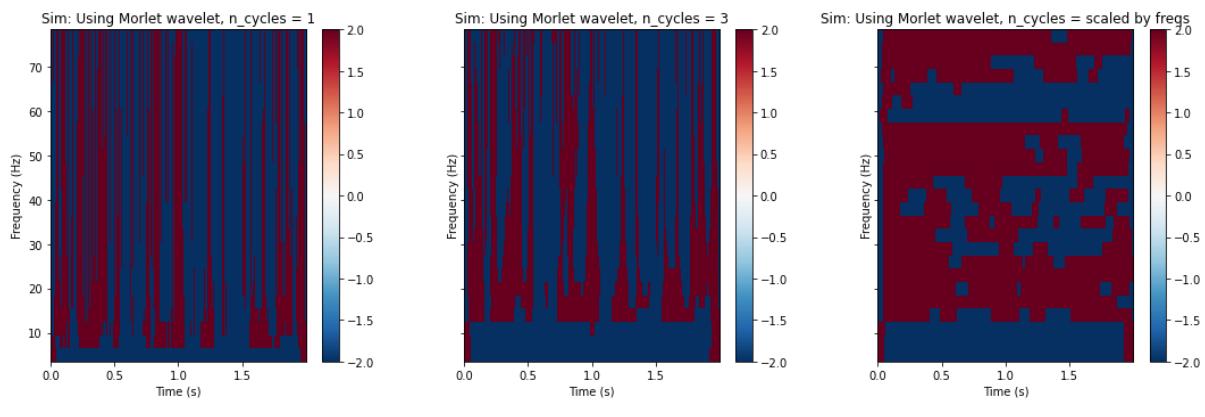
Useful Resource:

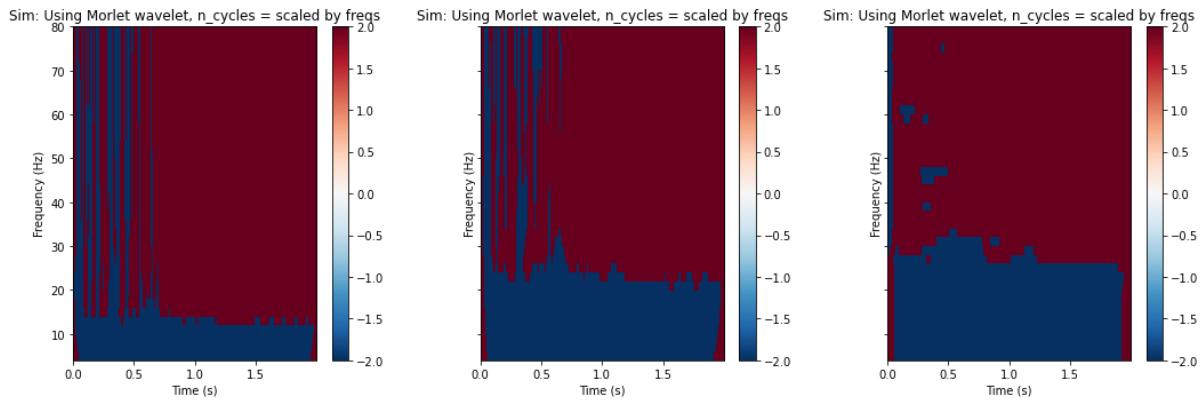
<https://www.youtube.com/playlist?list=PLtGXgNsNHqPTgP9wyR8pmy2EuM2ZGHU5Z>

(Playlist)

## 7.19 Discussion & Next step

1. literature review: the abstract of related papers can be found in the next page.
  - a. Survey the literature Xianhui & Nan
    - i. What's known?
    - ii. What has already been done?
    - iii. Previous models as a starting point?
    - iv. What hypotheses have been emitted in the field?
2. data analysis
  - a. we found DCM(Dynamic causal modeling) can be used only in the same trials. **How to quantify the differences/relationships of activation sequence across tasks in different trials** (discuss with mentor/project TA) Huayu
  - b. we found MNE required certain data structure. **How to transform the data shape to fit MNE, and then do the time-frequency analysis** Hanif & Ramy

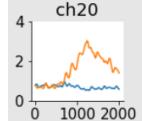




**subject 0 channel-20, hand real movement**

P.S. It's still messy :p, a lot of tuning & further preprocessing required

Note: found something somewhat interesting: More activity during hand movement basically corresponds to this graph



- c. we found SVM model showed near chance level in test dataset ([https://github.com/Xianhui-He/Raclette-Group-2-ECoG-Motor-Imagery/blob/main/SVM\\_pipeline\\_Xianhui.ipynb](https://github.com/Xianhui-He/Raclette-Group-2-ECoG-Motor-Imagery/blob/main/SVM_pipeline_Xianhui.ipynb)). **How to avoid overfitting of our classifier model**

- 3. focus on the first idea and the third idea

## 7.20 slides outline & mentor suggestions

mentor feedback:

1. **we have done a great job!** 🎉 🎉 🎉
2. ask more specific questions based on the previous results
3. reorganize the story
  - a. part 1: time frequency analysis for single channel mechanism (show what previous studies haven't done, like narrow band instead of rough band)
  - b. part 2: MVPA (multi-variate population analysis) for population mechanism
    - i. classifier (first raw broadband signal, then specific band signal based on the part 1)
    - ii. trajectory (first raw broadband signal, then specific band signal based on the part 1)
4. **focus more on the big picture!**

1. background (Nan & Xianhui)
  - a. which brain area does motor imagery recruit, compared to actual movement?
    - i. a large fronto-parietal network and motor-related area, but primary motor area (M1/precentral gyrus) does not show persistent activities (ref 2)
  - b. do motor imagery and actual movement have common neural correlates, or do they have distinct neural correlates?
    - i. they were similar in low frequency bands (alpha/beta, ref 3, 5, 6 & original), but differ in high frequency bands (original)
    - ii. also, the coupling between the phase of alpha (8–12 Hz) and the amplitude of high gamma (70–120 Hz) and this PAC decreases during motor imagery (ref 14)
  - c. do different motion types have common neural correlates, or do they have distinct neural correlates?
    - i. they were similar in low frequency bands, but may differ in high frequency bands (original)
2. our project idea (Nan & Xianhui)
  - a. Our group project wants to examine whether sensorimotor cortex represents motion types similarly in actual movement and imagery
    - i. hypothesis 1: no, they have distinct representations of motion types
    - ii. hypothesis 2: yes, they share similar representations though differ in the power
  - b. specifically, we want to ask two questions: 1) do actual movement and imagery differ in activation sequence/dynamics; 2) do actual movement and imagery differ in representation code
3. dataset introduction (Ramy)
  - a. what's the behavioral task? How many trials each task have?
  - b. how many subjects? how many channels each subject have in each roi?
  - c. do they preprocess the signals (notch filter, z-score...)
4. analysis pipeline
  - a. further preprocessing (band-pass filter) (Hanif)
  - b. ERP (Q1) (Hanif)
  - c. activation sequence/dynamics (Q1) (Huayu)
    - i. trajectory
  - d. time-frequency analys (Q1) (Hanif)
  - e. classifier (Q2) (Xianhui)

## Abstract/Proposal

### 1. Background

#### a. What is known

- Motor imagery is a significant part of movement (behavioural, psychological) (motor preparation)

- imagery recruits a large fronto-parietal network and motor-related area, but primary motor area (M1/precentral gyrus) does not show persistent activities (ref 2)

- Comparing MI and ME: Activation is similar in both lfb and hfb in (what) brain region (origional); while hand and tongue movement differs in HFB, but not in LFB

- b/ii ?

- b. What is not known**

- Differences and precise correlations between MI and ME

- Comparison of activation sequences of ROIs under MI and ME task

- Whether or not activation sequence contributes to the functional difference

## 2. Questions & Hypothesis

- a. Research Questions**

- If indeed different, what's the difference between activation sequence of areas of the brain of MI and ME?

- b. Hypothesis**

- Under MI and ME tasks, the sensorimotor cortex occupies a different position in the activation sequence, and projects a difference in its representation code.

## 3. Analysis pipeline

- a. Single-channel analysis**

- to understand the details:
  - ERP
  - time-frequency analysis

- b. Population level analysis**

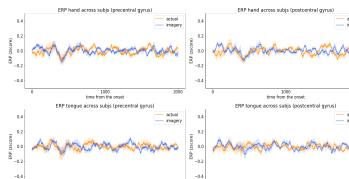
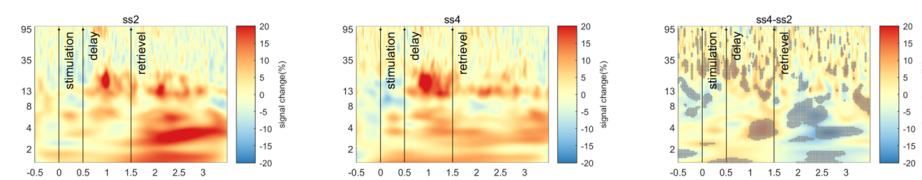
- to look at the big picture:
  - activation trajectory
  - classifier

## 4. Future Questions

- How does the activation difference correlate to functional differences?

- Why do they differ?

## 7.21 schedule

- 1) proposal/abstract writing (Huayu & Nan)
  - a) each one write a version of proposal
- 2) data-analysis
  - a) erp (done)
    - i) *what we can get from this analysis*
      - (1) *Neurophysiological changes in the brain during cognition (broadband signal)*
    - ii) *results*
      - iii)
  - b) time-frequency (need to check the code) (Xianhui & Hanif)
    - i) *what we can get from this analysis*
      - (1) *Simultaneous description of the power of a signal at different times and frequencies*
    - ii) *ideal results (left: hand ME; middle: hand MI; right: ME-MI (hand), example* 
    - iii)
  - c) classifier (need to add regularizer to the current pipeline) (Xianhui)
    - i) *what we can get from this analysis*
      - (1) *whether we can predict motion types from neural activities*
      - (2) *whether ME and MI share the representation of motion types*
  - d) trajectory (need a pipeline, PCA/t-SNE) (Ramy)
    - i) *what we can get from this analysis*

(1)

ii) *demo can be found in W1D5 Tutorial 3 Section 3.2*

discuss at 10 am UTC + 8

## 7.22 schedule (abstract deadline)

- 1) proposal/abstract writing (Xianhui & Nan)
  - a) each one write a version
- 2) data-analysis
  - a) fft (Hanif)
  - b) classifier (Xianhui)
  - c) neural trajectory (Huayu & Ramy)

## Abstract

### Abstract 0.0

From Miller et al (2010), they found that the spatial distribution of different movements types did not overlap in high frequency, but in low frequency band when comparing actual movements and motor imagery. .

Therefore, the current study aim to examine how actual movements and imagery movements differ in representing motion types. We addressed this question from activation pattern and temporal perspective.

To investigate the activation pattern, at individual level, time frequency analysis was performed to see XXX; at population level, we establish the model using the classifier to XXX.

To investigate the temporal difference, we also performed the trajectory analysis to see whether the motion types activate in the same sequence between actual movements and imagery movements.

## Group 1 Example:

1. (Environment) ECoG-based human motion prediction aims to predict future motion frames to guide various brain-computer interaction tasks.
2. (Prior Study and disadvantage) Most of the previous work has focused on solving this time series prediction task using RNN-based frameworks.
3. (Our improvement) Here, we propose a CNN-based prediction framework that not only predicts finger flexion movements, but also localizes electrodes that provide salient information for each finger's motion prediction task.
4. (Method Introduce) Specifically, we transformed 3-D ECoG signal as the input of CNN model. Our objective is to predict which finger is flexing. Meanwhile, by performing Class Activation Mapping(CAM), we can localize which electrodes the model is focusing on based on the current prediction task( e.g. If the data is collected during the flexion of index finger, then we can say the electrodes located by CAM and the brain areas where the electrode is implanted in provide the salient information for predicting the motion of index finger).
5. (Significance) This can provide important information for neural computing, neurophysiological surgery, and neural circuit analysis.

## Abstract 1.0

Imagery of motor movement plays an important role in preparing actual movement and learning of complex motor skills. Recent work suggested the power of both low-frequency band (8-32Hz) and high-frequency band (76-100Hz) in sensorimotor cortex as the neural correlates underlying the actual movement and imagery(specify, low frequency similar, high frequency different). However, it remains largely unknown how the information of motion types can be read out from these neural activities(focus on the imagery).

The present study examined whether imagery movement share the similar mechanism with actual movement at different levels. (introduce the dataset/general task/data type). First, we investigated the channel-level mechanism by looking at the differences between actual movement and imagery in the power of specific frequency bands, ie. alpha/beta/gamma. Second, we investigated the population-level mechanism by performing multi-variate classification and neural trajectory analysis. Specifically, we trained the classifier on actual movement/imagery and tested it on imagery/actual movement to see whether the classifier can be generalized to each other. Also, using t-SNE, we examined whether the imagery movement and actual movement activated in the same sequence at the neural subspace.

Our results (may) suggest motor imagery and actual movement both have the same neural substrates and distinctive neural representations at channel-level and population-level.

## Updated Abstract 1.1

Imagined motor movement (“Imagery”) plays a crucial role in preparing actual movements and learning of complex motor skills. Miller et al (2010) found that, when comparing actual

**movements and imagery, the spatial distribution of activities for different movements types did not overlap in high frequency(76-100Hz), but in low frequency band (8-32Hz).** However, it remains largely unknown what the neural activities of imagery look like compared with the actual movement.

The present study examined whether imagery shares similar mechanisms with actual movement at different levels. We used one of several ECoG datasets collected in a clinical setting with a variety of tasks, which consists of two blocks: actual movements and imagery (Miller, 2019). Eight patients (2 females; age range: 12-48) participated in these simple motor and imagery tasks. On one hand, we investigated the channel-level mechanisms by looking at the differences between actual movement and imagery in the power of specific frequency bands ( i.e. alpha/beta/gamma). On the other hand, we investigated the population-level mechanism by performing the multivariate classification and the neural trajectory analysis. Specifically, we trained the classifier on actual movement/imagery and tested it on imagery/actual movement to see whether the classifier can be generalized to each other. Also, using t-SNE, we examined whether the imagery and actual movement activated in the same sequence at the neural subspace.

Our results (may) suggest motor imagery and actual movement both have the same neural substrates and distinctive neural representations at both channel-level and population-level.

(275words)

Do you think it is better to use “imagery movement”?

I have checked the original paper, they seems used “imagery” often, and use “motor imagery” once. The thing is that we define “imagery” in our first sentence. I think it should be fine?

## Updated Abstract 1.2

Imagined motor movement (“Imagery”) plays a crucial role in preparing actual movements and learning of complex motor skills. Recent work suggested the power of both low-frequency band (8-32Hz) and high-frequency band (76-100Hz) in sensorimotor cortex as the neural correlates underlying the actual movement and imagery. Miller et al (2010) found that, when comparing actual movements and imagery, the spatial distribution of activities for different movements types did not overlap in high frequency, but in low frequency band. **(combine them into one sentence)** However, the neural substrates and neural representations of imagery remain largely unknown.

The present study examined whether imagery shares similar mechanisms with actual movement at different levels. With electrocorticography (ECoG) dataset in seven human subjects during actual movement and kinesthetic imagery of the same motion type (hand & tongue), we investigated the channel-level mechanisms by looking at the differences between actual movement and imagery in the power of specific frequency bands (i.e. alpha/beta/gamma). Furthermore, we investigated the population-level mechanism by performing the multivariate classification and the neural trajectory analysis. Specifically, we trained the classifier on actual movement/imagery and tested it on imagery/actual movement

to see whether the classifier can be generalized to each other. Also, using t-SNE, we examined whether the imagery and actual movement activated in the same sequence at the neural subspace.

Our results (may) suggest motor imagery and actual movement both have the same neural substrates and distinctive neural representations at both channel level and population level.

## Updated Abstract 1.3

Title: Does Imagery share similar neural mechanisms with the actual movement?

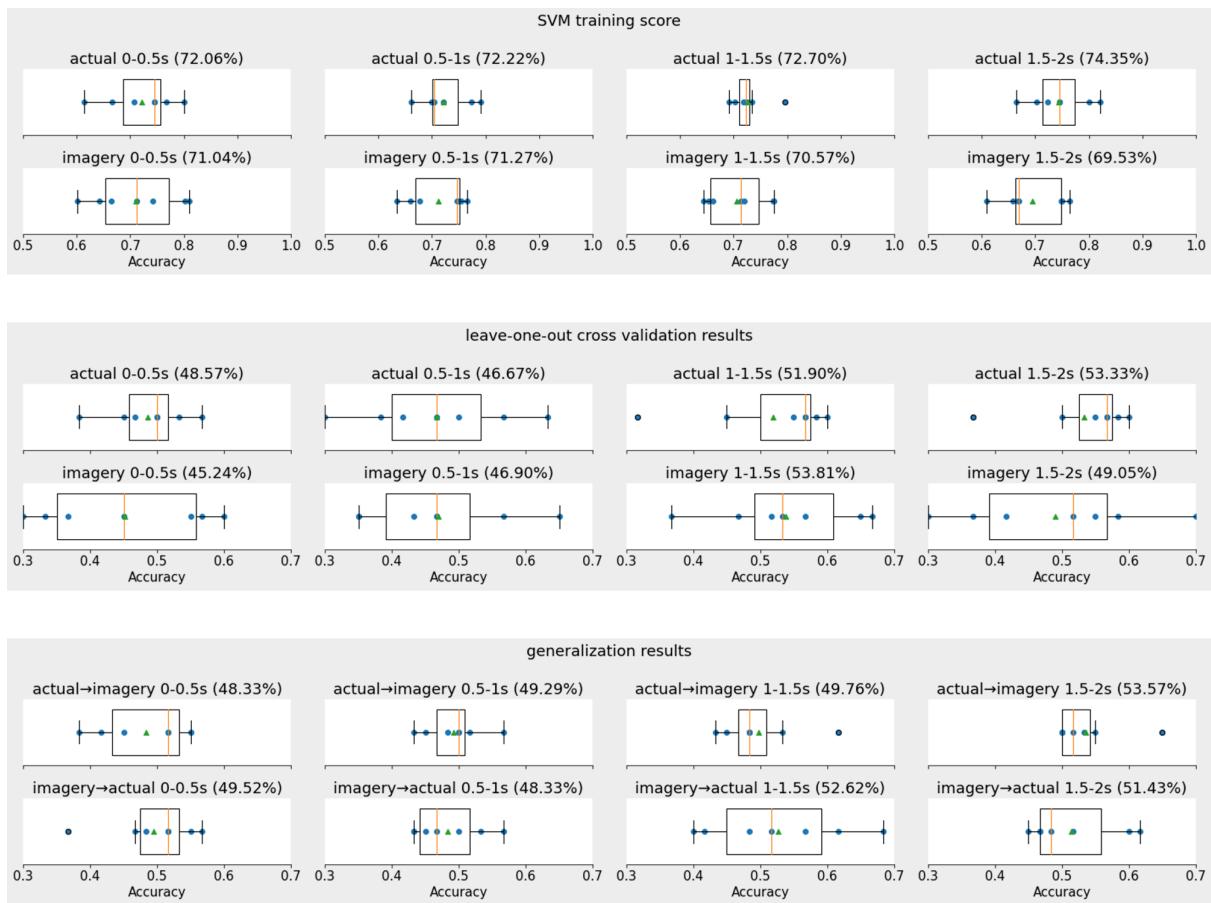
Imagined motor movement (“Imagery”) plays a crucial role in preparing actual movements and learning of complex motor skills. Miller et al (2010) have shown that the spatial distribution of activities in the primary motor area for imagery and actual movements does not overlap in high frequency (76-100Hz), but in low frequency band (8-32Hz). However, the neural substrates and neural representations of imagery still remain largely unknown.

The present study examined whether imagery shares similar mechanisms with actual movement at different levels. With electrocorticography (ECoG) dataset in seven human subjects during actual movement and kinesthetic imagery of the same motion type (hand & tongue), we investigated the channel-level mechanisms by looking at the differences between actual movement and imagery in the power of specific frequency bands (i.e. alpha/beta/gamma). Furthermore, we investigated the population-level mechanism by performing the multivariate classification and the neural trajectory analysis. Specifically, we trained the classifier on actual movement/imagery and tested it on imagery/actual movement to see whether the decoding can be generalized to each other. Also, using t-SNE, we examined whether the imagery and actual movement activated in the same sequence at the neural subspace.

Our results (may) suggest that in addition to common neural substrates shared by imagery and actual movements, there also exists imagery-specific neural substrates at both the channel level and the population level.

Keyword: electrocorticography (ECoG) | time frequency analysis | multivariate classification | neural trajectory analysis

word count: 224 words



## 7.25 schedule

- 1) presentation preparation (Hanif, Huayu, Nan & Ramy)
- 2) data analysis
  - a) fft (Hanif)
    - i) obtain the power matrix of every subject  
[ele][motion-imagery][trial][frequency][time]
  - b) classifier (Xianhui)
    - i) fit the power data for each band
  - c) neural trajectory (Huayu & Ramy)
    - i) draw the neural trajectory for each condition

discuss at 10 am UTC + 8

## 7.26 schedule

- 1) presentation preparation (one slide one person one minute)

- a) intro (Nan)
  - b) method (Ramy)
  - c) tft (Hanif)
  - d) classifier (Xianhui)
  - e) trajectory (Huayu)
  - f) conclusion (Huayu)
- 2) data analysis
- a) tft (Hanif)
    - i) obtain the power matrix of every subject and draw the figure  
[ele][motion-imagery][trial][frequency][time]
    - ii)
  - e) classifier (Xianhui)
    - i) fit the power data for each band
  - f) neural trajectory (Huayu & Ramy)
    - i) draw the neural trajectory for each condition

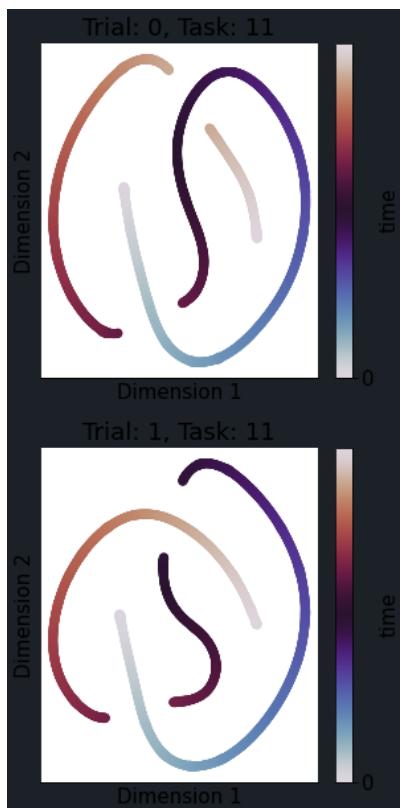
### 3) meeting with mentor (10 am UTC + 8)

- a) discuss within the group (9:30 am UTC + 8)

## 7.27 schedule

- 1) presentation preparation (one slide one person one minute)
  - a) intro (Nan)
  - b) method (Data) (Ramy)
  - c) tft (Hanif)
  - d) classifier (Xianhui)
  - e) trajectory (Huayu)
  - f) conclusion (Huayu)
- 2) data-analysis
  - a) tft (Hanif)
    - i) obtain the power matrix of every subject and draw the figure  
[ele][motion-imagery][trial][frequency][time]
    - ii)
  - b) classifier (Xianhui)
    - i) fit the power data for each band (0-1s; 1-2s)
  - c) neural trajectory (Huayu & Nan) try power data for each band

- i) extract time window
- ii) make figure illustrative
- iii) find "Loading Matrix" to find the contribution of different electrodes
- iv) three dimension



# Literature review:

the differences in the neural correlates (ERP/frequency signals/function connectivity/activation/power/phase etc) between actual movement and imagery movement

## **1. \*\*Induced Gamma-Band Activity during Actual and Imaginary Movements: EEG Analysis**

The purpose of this paper is to record and analyze induced gamma-band activity (GBA) (30–60 Hz) in cerebral motor areas during imaginary movement and to compare it quantitatively with activity recorded in the same areas during actual movement using a simplified electroencephalogram (EEG). Brain activity (basal activity, imaginary motor task and actual motor task) is obtained from 12 healthy volunteer subjects using an EEG (Cz channel). GBA is analyzed using the mean power spectral density (PSD) value. Event-related synchronization (ERS) is calculated from the PSD values of the basal GBA (GBAb), the GBA of the imaginary movement (GBAim) and the GBA of the actual movement (GBAac). The mean GBAim and GBAac values for the right and left hands are significantly higher than the GBAb value ( $p = 0.007$ ). No significant difference is detected between mean GBA values during the imaginary and actual movement ( $p = 0.242$ ). The mean ERS values for the imaginary movement (ERSimM (%)) = 23.52) and for the actual movement (ERSacM = 27.47) do not present any significant difference ( $p = 0.117$ ). We demonstrated that ERS could provide a useful way of indirectly checking the function of neuronal motor circuits activated by voluntary movement, both imaginary and actual. These results, as a proof of concept, could be applied to physiology studies, brain–computer interfaces, and diagnosis of cognitive or motor pathologie

## **2. \* (review paper)The neural network of motor imagery: An ALE meta-analysis**

Motor imagery (MI) or the mental simulation of action is now increasingly being studied using neuroimaging techniques such as positron emission tomography and functional magnetic resonance imaging. The booming interest in capturing the neural underpinning of MI has provided a large amount of data which until now have never been quantitatively summarized. The aim of this activation likelihood estimation (ALE) meta-analysis was to provide a map of the brain structures involved in MI. Combining the data from 75 papers revealed that MI consistently recruits a large fronto-parietal network in addition to subcortical and cerebellar regions. Although the primary motor cortex was not shown to be consistently activated, the MI network includes several regions which are known to play a role during actual motor execution. The body part involved in the movements, the modality of MI and the nature of the MI tasks used all seem to influence the consistency of activation within the general MI network. In addition to providing the first quantitative cortical map of MI, we highlight methodological issues that should be addressed in future research.

## **3. \*\*\*Relationship between Speed and EEG Activity during Imagined and Executed Hand Movements**

we investigated the relationship between the kinematics of imagined and actual hand movement, i.e. the clenching speed, and the EEG activity in ten human subjects. Study participants were asked to perform and imagine clenching of the left hand and right hand at various speeds. The EEG activity in the alpha (8 Hz – 12 Hz) and beta (18 Hz – 28 Hz) frequency bands were found to be linearly correlated with the speed of imagery clenching. Similar parametric modulation was also found during the execution of hand movements. A single equation relating the EEG activity to the speed and the hand (left vs. right) was developed. This equation, which contained a linear independent combination of the two parameters, described the time-varying neural activity during the tasks. Based on the model, a regression approach was developed to decode the two parameters from the multiple-channel EEG signals. We demonstrated

the continuous decoding of dynamic hand and speed information of the imagined clenching. In particular, the time-varying clenching speed was reconstructed in a bell-shaped profile. Our findings suggest an application to providing continuous and complex control of non-invasive brain-computer interface for movement-impaired paralytics.

#### **4. Evaluation of Kinesthetic/Visual Motor Imagery of Dorsiflexion of the Right Ankle Joint via Event-Related Desynchronization/Synchronization (2019)**

Motor imagery, which is an image of movement without actual motion, is divided into kinesthetic or visual motor imagery (K/VMI). KMI is known to show brain activities that are closer to those associated with actual movement than VMI. Therefore, it is suggested that KMI is useful for rehabilitation of patients with stroke hemiplegia. The purpose of this study was to evaluate K/VMI using a questionnaire and an event-related desynchronization/synchronization (ERD/S). Eight healthy males (21 to 26 years old) were asked to perform K/VMI or movement execution/observation (ME/O) of the dorsiflexion of the right ankle joint and non-motor imagery (NMI) as tasks. Time-frequency analysis of electroencephalograms of the task was conducted via short-time Fourier transformation. Then, ERD/S (the change rate of the power spectral density compared to the resting state) was calculated. Furthermore, spatiotemporal analysis of ERD/S was performed in the alpha (10 to 13 Hz) beta (13 to 35 Hz) bands. As a result, it is suggested that K/VMI evaluation using a questionnaire could be achieved from spatiotemporal ERD/S by noting the differences in KMI vs. VMI, KMI vs. ME, and VMI vs. MO.

#### **5. On the Correlations of Motor Imagery of Swallow with Motor Imagery of Tongue Movements and Actual Swallow**

This paper investigated the correlations between motor imagery of swallow (MI-SW) and motor imagery of tongue movements (MI-Ton), and correlations between MI-SW and actual swallow (Act-SW). EEG data of 10 healthy subjects and one dysphagia patient were collected and analyzed. The group analysis results of using bin-based spectral power demonstrated that MI-SW and MI-Ton, and MI-SW and Act-SW were strongly correlated ( $p$ -value < 0.001, examined Inat 'C3') for both mu and low beta frequency bands. Further, the correlation was weaken but still significant for MI-SW and Act-SW ( $p$ -value < 0.05), and MI-SW and MI-Ton ( $p$ -value < 0.01) for the dysphagia patient. These results validated the use of MI-SW and MI-Ton for dysphagia rehabilitation.

**6. Mu and beta rhythm topographies during motor imagery and actual movements** People can learn to control the 8-12 Hz mu rhythm and/or the 18-25 Hz beta rhythm in the EEG recorded over sensorimotor cortex and use it to control a cursor on a video screen. Subjects often report using motor imagery to control cursor movement, particularly early in training. We compared in untrained subjects the EEG topographies associated with actual hand movement to those associated with imagined hand movement. Sixty-four EEG channels were recorded while each of 33 adults moved left- or right-hand or imagined doing so. Frequency-specific differences between movement or imagery and rest, and between right- and left-hand movement or imagery, were evaluated by scalp topographies of voltage and r spectra, and principal component analysis. Both movement and imagery were associated with mu and beta rhythm desynchronization. The mu topographies showed bilateral foci of desynchronization over sensorimotor cortices, while the beta topographies showed peak desynchronization over the vertex. Both mu and beta rhythm left/right differences showed bilateral central foci that were stronger on the right side. The independence of mu and beta rhythms was demonstrated by differences for movement and imagery for the subjects as a group and by principal components analysis. The results indicated that the effects of imagery were not simply an attenuated version of the effects of movement. They supply evidence that motor imagery could play an important role in EEG-based communication, and suggest that mu and beta rhythms might provide independent control signals.

## **7. Modulation of EMG power spectrum frequency during motor imagery**

To provide evidence that motor imagery (MI) is accompanied by improvement of intramuscular conduction velocity (CV), we investigated surface electromyographic (EMG) activity of 3 muscles during the elbow flexion/extension. Thirty right-handed participants were asked to lift or to imagine lifting a weighted dumbbell under 3 types of muscular contractions, i.e. concentric, isometric and eccentric, taken as independent variables. The EMG activity of the agonist (long and short heads of biceps brachii) and the antagonist (long portion of triceps brachii) muscles was recorded and processed to determine the median frequency (MF) of EMG power spectrum as dependant variable. The MF was significantly higher during the MI sessions than during the resting condition while the participants remained strictly motionless. Moreover, the MF during imagined concentric contraction was significantly higher than during the eccentric. Thus, the MF variation was correlated to the type of contraction the muscle produced. During MI, the EMG patterns corresponding to each type of muscle contraction remained comparable to those observed during actual movement. In conclusion, specific motor programming is hypothesized to be performed as a function of muscle contraction type during

## **8. A frequency-temporal-spatial method for motor-related electroencephalography pattern recognition by comprehensive feature optimization**

Either imagined or actual movements lead to a combination of electroencephalography signals with distinctive frequency, temporal and spatial characteristics, which correspond to various motor-related neural activities. This frequency-temporal–spatial pattern is the key of motor intention decoding which is the basis of brain–computer interfaces by motor imagery. We present a new method for motor-related electroencephalography recognition which comprehensively optimizes the frequency–time–space features in a user-specific way. The recognition work focuses on three points: proper time and frequency domain segmentation, spatial optimization based on common spatial pattern filters and feature importance evaluation. We show that by combining the advantages of these optimizational methods, the proposed algorithm effectively improves motor task classification, and the recognized signal characteristics can be used to visualize the motor related electroencephalography patterns under different conditions.

## **9. Multiband tangent space mapping and feature selection for classification of EEG during motor imagery**

**Objective.** When designing multiclass motor imagery-based brain-computer interface (MI-BCD, a so-called tangent space mapping (TSM) method utilizing the geometric structure of covariance matrices is an effective technique. This paper aims to introduce a method using ISM for finding accurate operational frequency bands related brain activities associated with MI tasks. **Approach.** A multichannel electroencephalogram (EEG) signal is decomposed into multiple subbands, and tangent features are then estimated on each subband. A mutual information analysis-based effective algorithm is implemented to select subbands containing features capable of improving motor imagery classification accuracy. Thus obtained features of selected subbands are combined to get feature space. A principal component analysis-based approach is employed to reduce the features dimension and then the classification is accomplished by a support vector machine (SVM). **Main results.** Offline analysis demonstrates the proposed multiband tangent space mapping with subband selection (MTSMS) approach outperforms state-of-the-art methods. It achieves the highest average classification accuracy for all datasets (BCI competition dataset 2a, ilia, IIIb, and dataset JK-HH1). **Significance.** The increased classification accuracy of MI tasks with the proposed MTSMS approach can yield effective implementation of BCE. The mutual information-based subband selection method is implemented to tune operation frequency bands to represent actual motor imagery tasks.

## **10. Induced Gamma-Band Activity during Actual and Imaginary Movements: EEG Analysis**

The purpose of this paper is to record and analyze induced gamma-band activity (GBA) (30-60 Hz) in cerebral motor areas during imaginary movement and to compare it quantitatively with activity recorded in the same areas during actual movement using a simplified electroencephalogram (EEG). Brain activity (basal activity, imaginary motor task and actual motor task) is obtained from 12 healthy volunteer subjects using an EEG (Cz channel). GBA is analyzed using the mean power spectral density (PSD) value. Event-related synchronization (ERS) is calculated from the PSD values of the basal GBA (GBAb), the GBA of the imaginary movement (GBAim) and the GBA of the actual movement (GBAac). The mean GBAim and GBAac values for the right and left hands are significantly higher than the GBAb value ( $p = 0.007$ ). No significant difference is detected between mean GBA values during the imaginary and actual movement ( $p = 0.242$ ). The mean ERS values for the imaginary movement (ERSimM (%)) = 23.52) and for the actual movement (ERSacM = 27.47) do not present any significant difference ( $p = 0.117$ ). We demonstrated that ERS could provide a useful way of indirectly checking the function of neuronal motor circuits activated by voluntary movement, both imaginary and actual. These results, as a proof of concept, could be applied to physiology studies, brain-computer interfaces, and diagnosis of cognitive or motor pathologies

## **11. Structural and Functional Peculiarity of Brain Activity to Performance and Imaginary Motor Tasks in Healthy Persons (EEG and fMRI study)**

Bioelectrical (EEG) and hemodynamic (fMRI-response) cerebral reactions to performance and imaginary motor tasks by right or left hand were analyzed in 15 right-handed healthy persons (21-39 years old). During actual movement the main fMRI-response was registered in the area of central gyrus of the hemisphere contralateral to the working hand. Areas of activation were also revealed in the supplemental motor area and the ipsilateral hemisphere of the cerebellum. EEG data showed coherence increase in high frequency alpha- and beta-bands in the activated hemisphere. In imaginary motor tasks the intensity and topography of fMRI-response became the more variable; response was decreased in the motor area and in cerebellum, they increased in the subcortical structures and in the parietal association zones. EEG changes were very variable in this situation also; it was observe an increase of EEG coherence in the right hemisphere for higher frequency of alpha and beta spectral bands Changes of power spectrum parameters were similar to performance and imaginary motor tasks. Spectrum power and middle frequency of beta band were increased. Topographically these changes did not correspond to activated hemisphere and it was more in the left hemisphere. These changes were reflected nonspecific component of reaction.

## **12. Motor Imagination of Lower Limb Movements at Different Frequencies**

Motor imagination (MI) is the mental process of only imagining an action without an actual movement. Research on MI has made significant progress in feature information detection and machine learning decoding algorithms, but there are still problems, such as a low overall recognition rate and large differences in individual execution effects, which make the development of MI run into a bottleneck. Aiming at solving this bottleneck problem, the current study optimized the quality of the MI original signal by "enhancing the difficulty of imagination tasks," conducted the qualitative and quantitative analyses of EEG rhythm characteristics, and used quantitative indicators, such as ERD mean value and recognition rate. Research on the comparative analysis of the lower limb MI of different tasks, namely, high-frequency motor imagination (HFMI) and low-frequency motor imagination (LFMI), was conducted. The results validate the following: the average ERD of HFMI (-1.827) is less than that of LFMI (-1.3487) in the alpha band, so did (-3.4756 < -2.2891) in the beta band. In the alpha and beta characteristic frequency bands, the average ERD of HFMI is smaller than that of LFMI, and the ERD values of the two are significantly different ( $p=0.0074<0.01$ ;  $r = 0.945$ ). The ERD intensity STD values of HFMI are less than those of LFMI. which suggests that the ERD intensity individual difference among the subjects is smaller in the HFMI mode than in the LFMI mode. The average recognition rate of HFMI is higher than that of LFMI (87.84% > 76.46%), and the recognition rate of the two modes is significantly different ( $p=0.0034<0.01$ ;  $r = 0.429$ ). In summary, this research optimizes the quality of MI brain signal sources by enhancing the difficulty of imagination tasks, achieving the purpose of

improving the overall recognition rate of the lower limb MI of the participants and reducing the differences of individual execution effects and signal quality among the subjects.

\*Frequency-Domain Energy Analysis and Results

\*Time-Frequency Diagram Analysis

### **13. Actual and mental motor preparation and execution: a spatiotemporal ERP study**

Studies evaluating the role of the executive motor system in motor imagery came to a general agreement in favour of the activation of the primary motor area (M1) during imagery, although in reduced proportion as compared to motor execution. It is still unclear whether this difference occurs within the preparation period or the execution period of the movement, or both. In the present study, EEG was used to investigate separately the preparation and the execution periods of overt and covert movements in adults. We designed a paradigm that randomly mixed actual and kinaesthetic imagined trials of an externally paced sequence of finger key presses. Sixty channel event-related potentials were recorded to capture the cerebral activations underlying the preparation for motor execution and motor imagery, as well as cerebral activations implied in motor execution and motor imagery.

Classical waveform analysis was combined with data-driven spatiotemporal segmentation analysis. In addition, a LAURA source localization algorithm was applied to functionally define brain related motor areas. Our results showed first that the difference between actual and mental motor acts takes place at the late stage of the preparation period and consists of a quantitative modulation of the activity of common structures in M1. Second, they showed that primary motor structures are involved to the same extent in the actual or imagined execution of a motor act. These findings reinforce and refine the functional equivalence hypothesis between actual and imagined motor acts.

### **14. .Alpha and high gamma phase amplitude coupling during motor imagery and weighted cross-frequency coupling to extract discriminative cross-frequency patterns**

Motor imagery modulates specific [neural oscillations](#) like actual movement does. Representatively, suppression of the alpha power (e.g., event-related desynchronization [ERD]) is the typical pattern of motor imagery in the [motor cortex](#). However, in addition to this amplitude-based feature, the coupling across frequencies includes important information about the brain functions and the existence of such complex information has been reported in various invasive studies. Yet, the interaction across multiple frequencies during motor imagery processing is still unclear and has not been widely studied, particularly concerning the non-invasive signals. In this study, we provide empirical evidence of the comodulation between the phase of [alpha rhythm](#) and the amplitude of high [gamma rhythm](#) during the motor imagery process. We used electroencephalography (EEG) in our investigation during the imagination of left- or right-hand movement recorded from 52 healthy subjects, and quantified the ERD of alpha and phase-amplitude coupling (PAC) which is a relative change of modulation index to the base line period (before the cue). As a result, we found that the coupling between the phase of alpha (8–12 Hz) and the amplitude of high gamma (70–120 Hz) and this PAC decreases during motor imagery and then rebounds to the baseline like alpha ERD ( $r = 0.29$  to  $0.42$ ). This correlation between PAC and ERD was particularly stronger in the ipsilateral area. In addition, trials that demonstrated higher alpha power during the ready period (before the cue) showed a larger ERD during motor imagery and similarly, trials with higher modulation index during the ready period yielded a greater decrease in PAC during imagery. In the classification analysis, we found that the effective phase frequency that showed better decoding accuracy in left and right-hand imagery, varied across subjects. Motivated by result, we proposed a weighted cross-frequency coupling (WCFC) method that extracts the maximal discriminative feature by combining band power and CFC. In the evaluation, WCFC with only two electrodes yielded a performance comparable to the conventional algorithm with 64 electrodes in classifying left and right-hand motor imagery. These results indicate that the phase-amplitude frequency plays an important role in motor imagery, and that optimizing this frequency ranges is crucial for extracting information features to decode the motor imagery types.

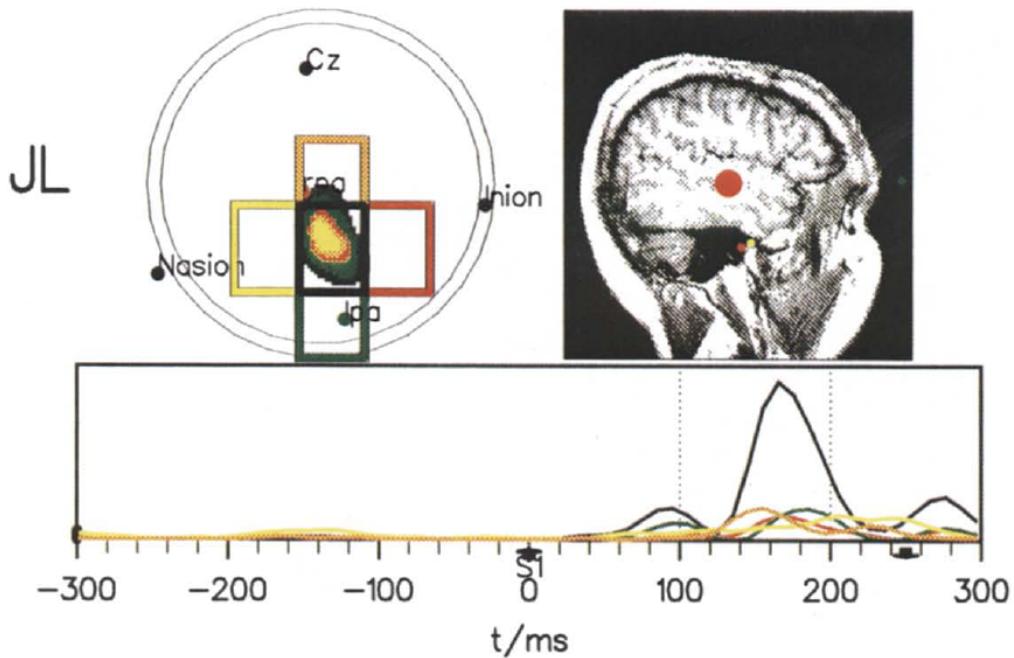
### **15. Do imagined and executed actions share the same neural substrate?**

- a. third experiment worth attention
- b. functional mapping of the regional cerebral blood flow (rCBF)
  - i. Ingvar and Philipsson [26] measured rCBF for the first time in human subjects who were instructed either to imagine a clenching hand movement with a slow rhythm, or actually to carry out the same movement. During mental simulation they found significant flow increases in the premotor and frontal regions. When the hand movements were actually carried out there was mainly an activation of the same magnitude in the contralateral primary motor cortex.
  - ii. more on page 90

## **16. Adaptive modelling of EEG signals to produce accurate time-frequency decompositions for use in BCI**

Motor imagery and actual movement are both tasks that bring forth a noticeable change in the subject's EEG mu rhythm known as Event-Related Desynchronisation (ERD). They appear as magnitude decreases of the frequencies included in the said band and can be tracked and measured for the automatic real-time detection and classification of the events. It has been proven that an important percent of the changes happen within a narrow frequency band called a reactive band, providing thus the means to significantly improve the efficiency of the interpretation of such events by concentrating the decisive information. The algorithm presented in this paper automatically identifies a subject's specific reactive band by detecting the highest decrease in power. The decision is made after the recorded EEG signal is modeled with a Band-Limited Multiple Fourier Linear Combiner (BMFLC). The method adaptively estimates the amplitude of each frequency component in the given band of interest and produces a precise time-frequency map that can be afterwards used for increasingly accurate classification and BCI applications.

# Quantifying Activation Sequence

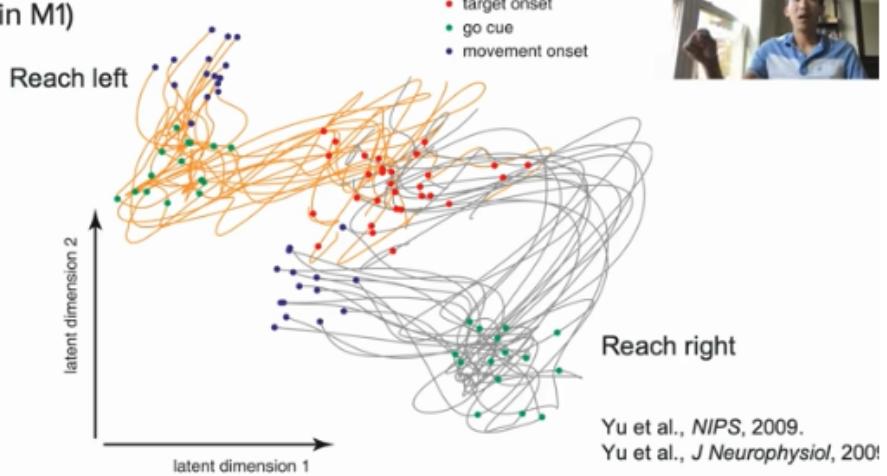


(Source: Activation sequence of discrete brain areas during cognitive processes: results from Magnetic field tomography, A.A. Ioannides, et al, 1994)

This is how you would visualize activation sequence. (This is from an ancient paper, so idk if there exists some better method.)

Another idea: use dimensionality reduction!

### Single-trial neural trajectories (using GPFA, 61 units in M1)



### 7.20 meeting notes with the mentor

- time frequency analysis- trajectory-decoding
  - population lvl / single-channel study

- time-frequency analysis (single channel mechanism)
- population analysis (population level mechanism)
  - raw broadband signal
  - specific band signal (trajectory?)
- analysis tft: what have we done, what kind of progress
  - method: classical classifier method/ check other paper
- specify our research q more clearly
- check frequency in narrow range

decoding-raw signal

trajectory- usually use raw signal

PCA can be used to check artifacts. (PCA denoising)

## 7.29 Archive assignment

Hanif Jupyter Link:

<https://colab.research.google.com/drive/1UULiYSv6nZkoP36zOeysCTahlhUV0Kcq?usp=sharing>

Xianhui Jupyter Link:

<https://colab.research.google.com/drive/1uvMhvG79c82Tz17Ww7ZzYgOmFcqWSeUg?usp=sharing>

Huayu Jupyter Link:

Nan Chen video Link:

- Hanif:
  - add documentation on jupyter notebook
  - give Ramy your jupyter notebook link (attach it above)
- Xianhui:
  - add documentation on jupyter notebook
  - give Ramy your jupyter notebook link (attach it above)
- Huayu:
  - add documentation on jupyter notebook
  - archive result and method figures on github repo
- Ramy:
  - update website result&method sections
  - add jupyter notebook link to website and write a intro/summary for it
  - add video embed in website
- Nanchen:
  - finish the record video
  - upload it to google drive/youtube
  - give the link to ramy (attach it above)

