Decoding multisensory attention from electroencephalography for use in brain-computer interface

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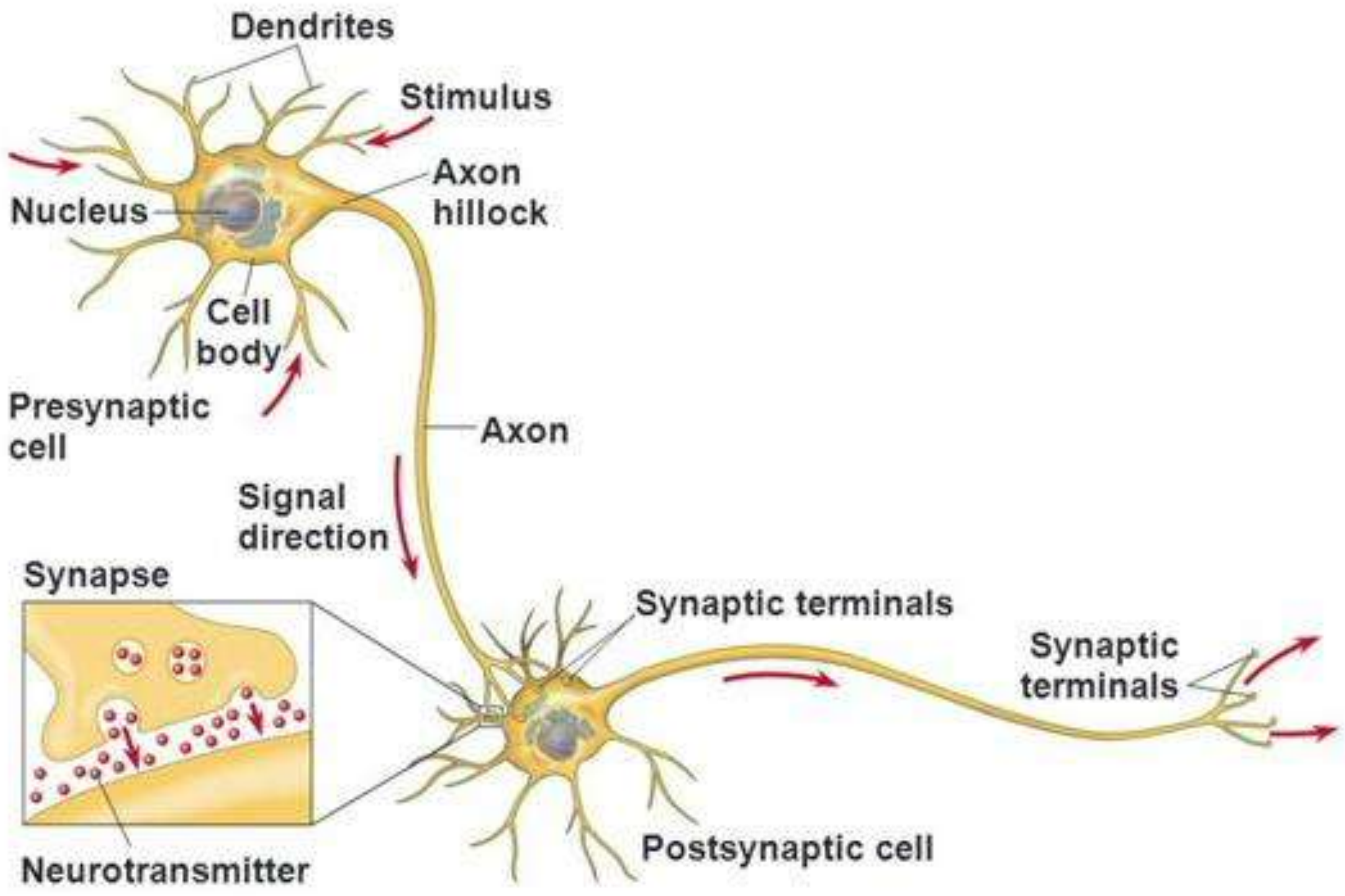
Agenda

- Introduction
  - Electroencephalography (EEG)
  - Brain-computer interface (BCI)
- Research objectives & literature review
- Experiment & equipment
- Signal processing and data analysis
- Results
- Conclusions & future works

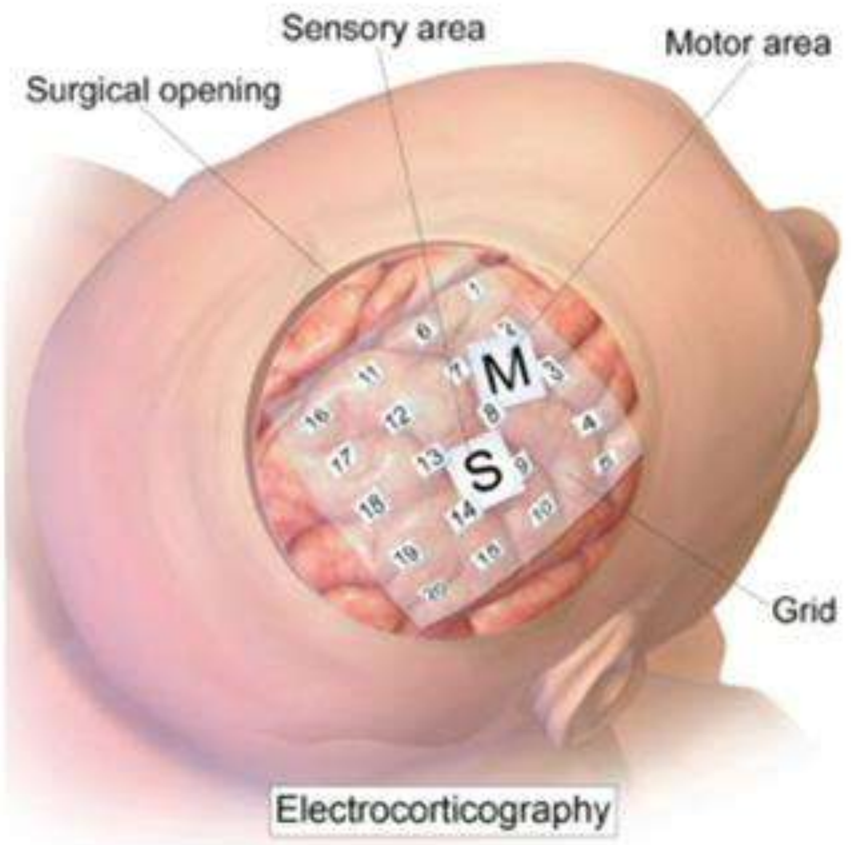
Neurons

- ~100 million – 100 billion neurons in a brain
- Chemical signal at synapses
- Electrical signal for long-distance communication



Electrocorticography (ECoG)

- Record electrical activity from the cortex
  - Invasive
- High temporal resolution
- High spatial resolution
- High signal-to-noise ratio

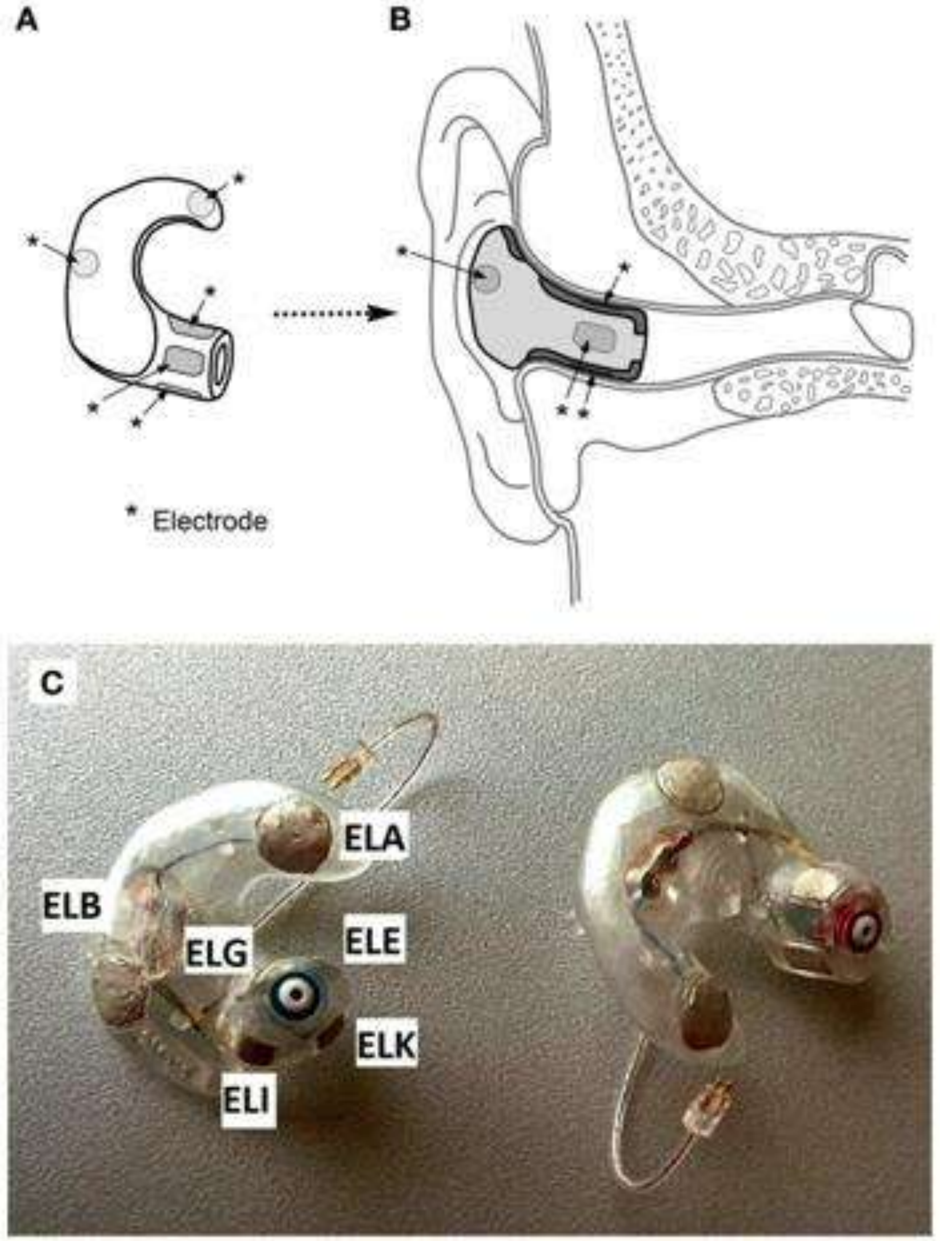


Surface electroencephalography (EEG)

- Electrical potential along the scalp (μV)
  - Non-invasive
- High temporal resolution (>1kHz)
- Low spatial resolution (cm)
- Low signal-to-noise ratio (<0dB)

In-ear EEG

- Measure EEG signal in/around the ear
- Pros
  - Unobtrusive
  - Consistent placement
- Cons
  - Even lower signal-to-noise ratio
  - No spatial information



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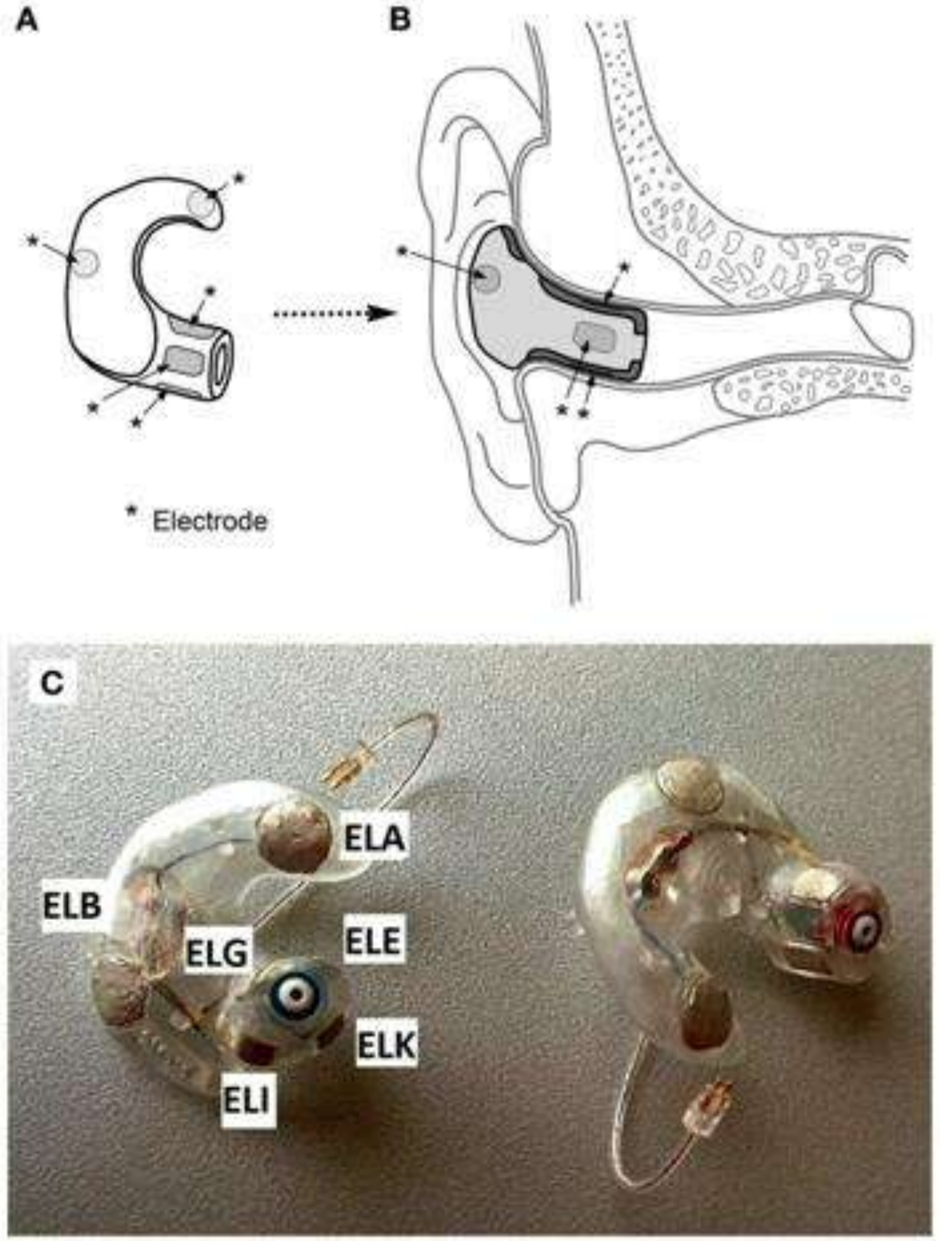

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Brain-computer Interface (BCI)

- Definition: A communication or control system that allows **real-time** interaction between the human brain and the external devices[2].
- Applications
  - Medical: ECoG during surgery
  - Psychological: stress and emotion monitoring
  - Interactive: translate brain state to a command or an action

BCI paradigms

Paradigms		Task	Cons	Information transfer rate (ITR)
Motor Imagery	Sensorimotor Rhythms	Imagining body parts movement	Weeks/Months of training[5]	~20 bits/min[3]
	Imagined Body Kinematics	Imagining continuous movement of only one body part	Usually used in ECoG, poor decoding in EEG[4]	NA
External Stimulation	Visual P300	Focus on a visual object with infrequently presented events	Visual focus required[5]	15-25 bits/min[5]
	Steady-state Visual Evoked Potential (SSVEP)	Focus on a flickering object	Fatigue due to flickering[5]	~20 bits/min[6]
	Auditory Steady-state Response (ASSR)	Attention to pure tone with a constant modulation frequencies	Low performance[5]	~1.5 bits/min[6]
	Steady-state Somatosensory Evoked Potential (SSSEP)	Attention to vibration with a constant (modulation) frequency	Low performance	~1.5 bits/min [6]

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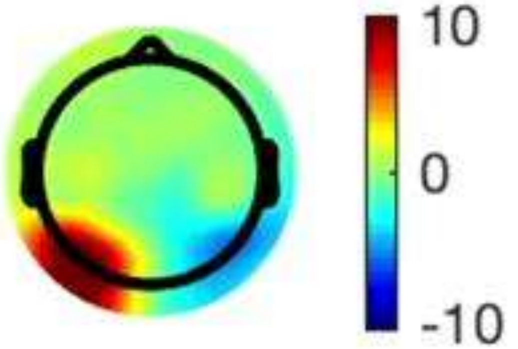
Research objectives

- Investigate the feasibility of using audio and tactile stimuli to build a functional BCI system
- Investigate the feasibility of using a interactive task-based paradigm for BCI system
- Compare the attention decoding between using audio and tactile stimuli

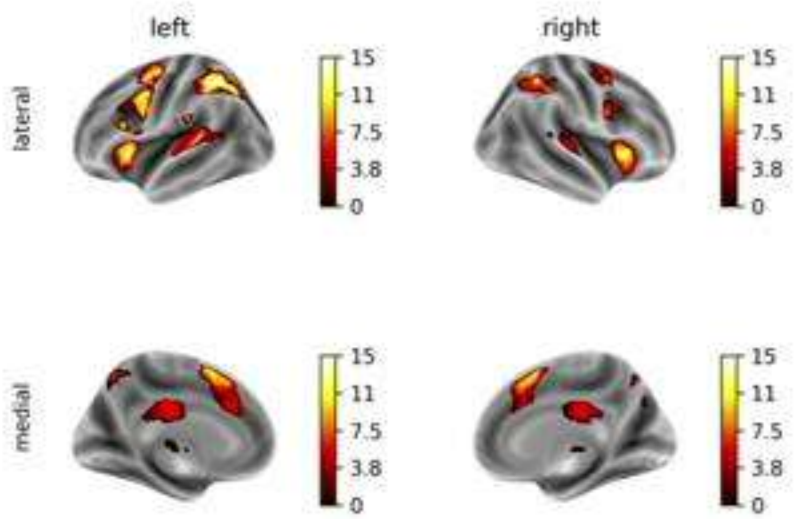
Literature review: decode auditory attention

- Auditory spatial attention
  - Power increase in the (8-14Hz) band
  - Detectable on group average level

Attend left – Attend right



Spatial > Control



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Literature review: decode auditory attention

- Auditory spatial attention
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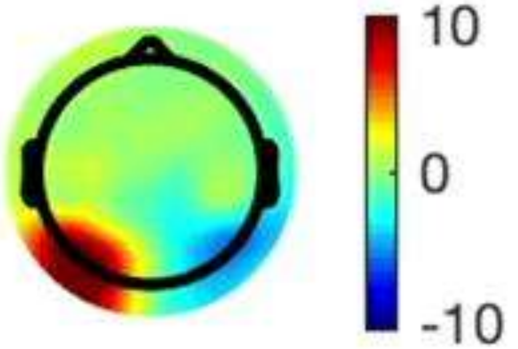
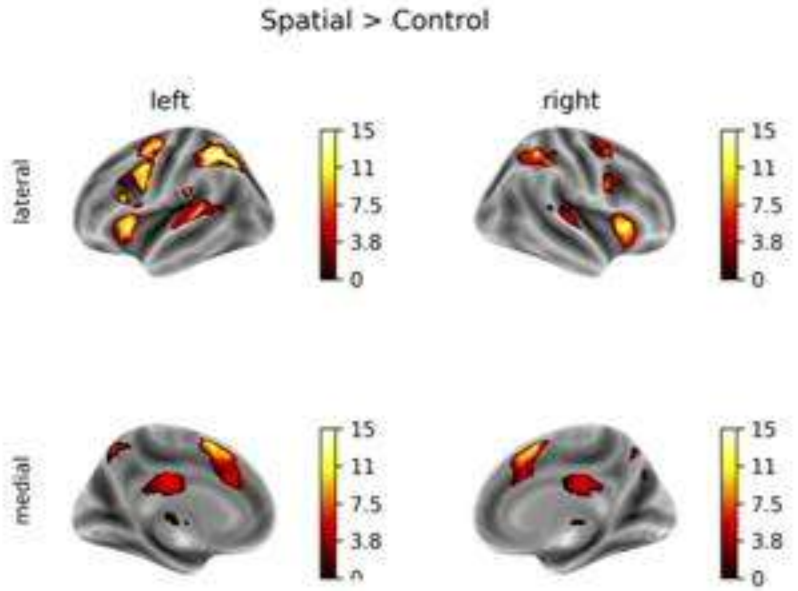
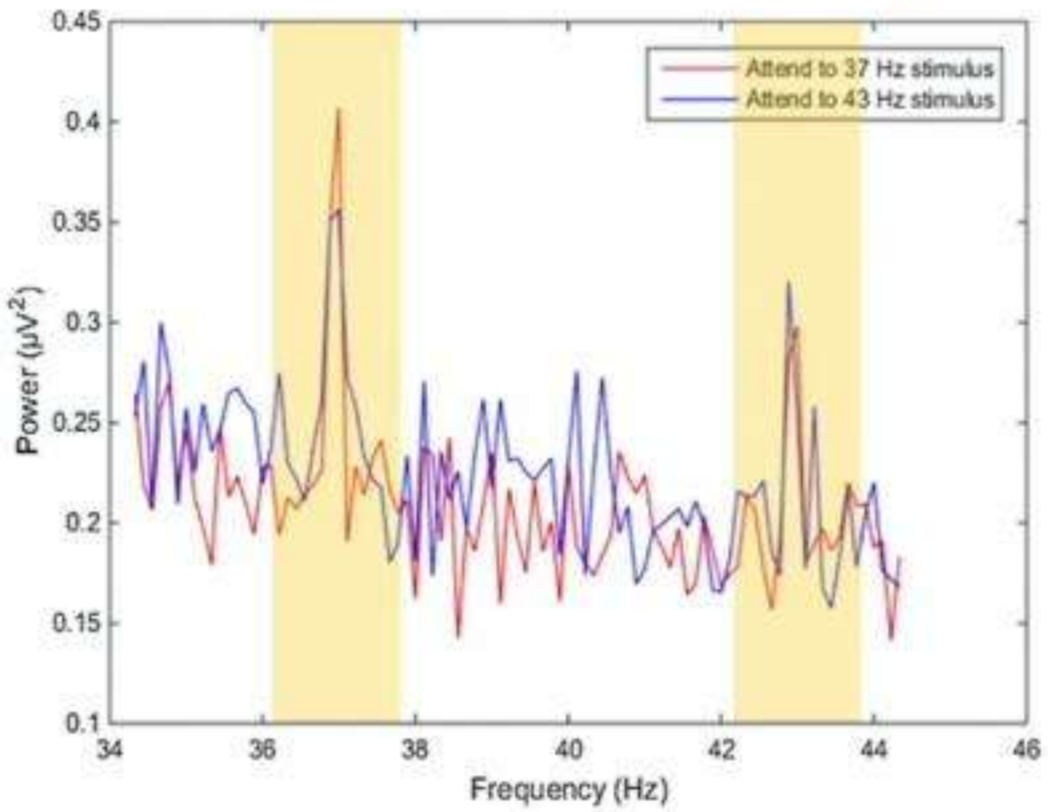
- Auditory steady-state response
  - Power increase at the modulation frequency of the attended stream

Attend left – Attend right







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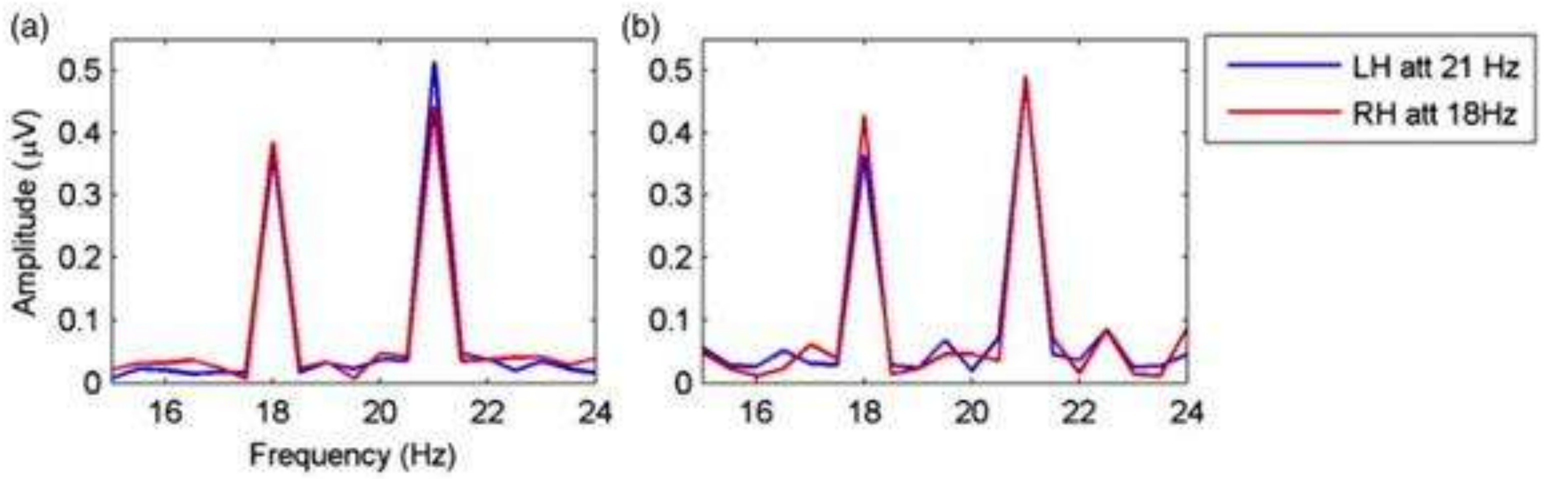
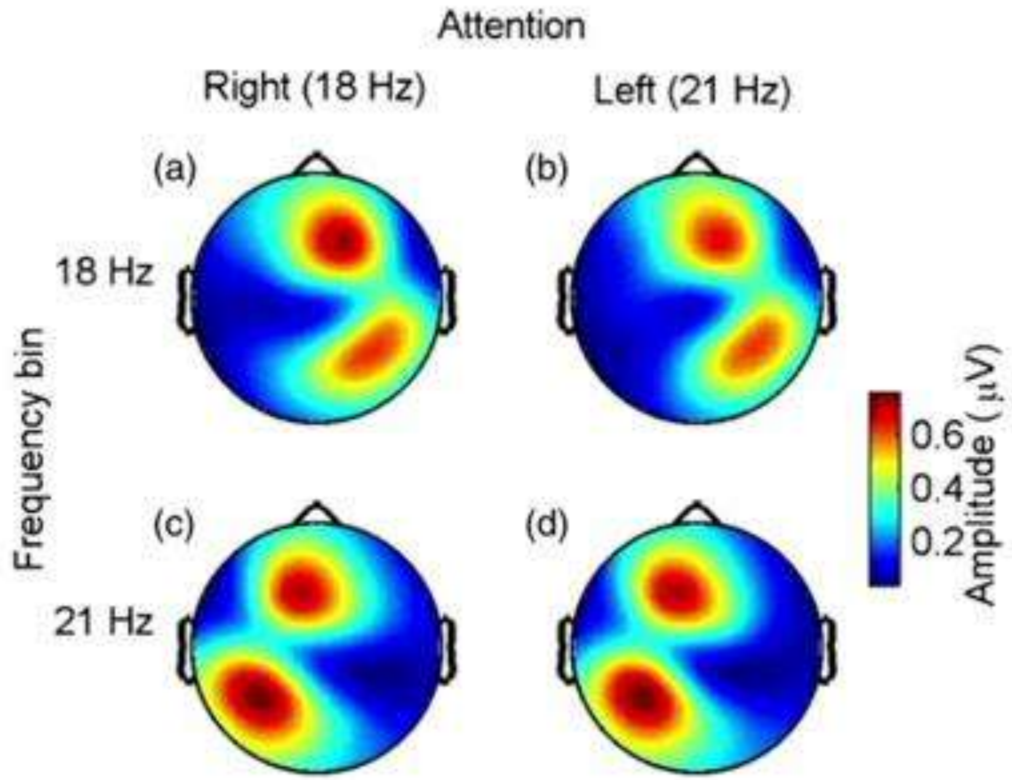
Literature review: decode tactile attention

- Steady-state somatosensory evoked potential (SSSEP)
  - Vibration at fingers
  - Power increase at the modulation frequency of the attended vibration





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Interactive task-based paradigm

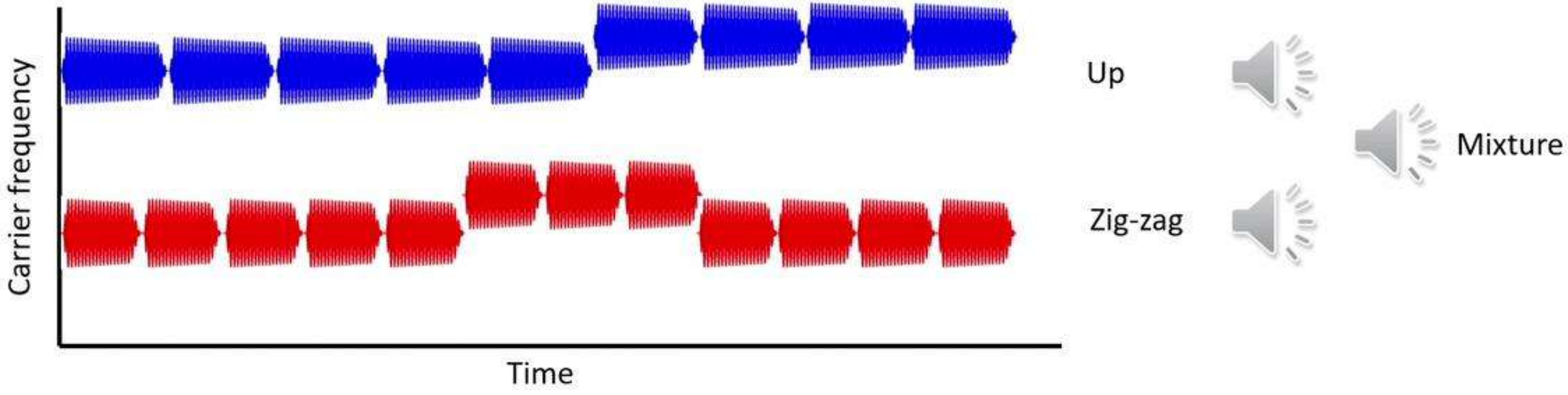
- Require a response from the subject during the experiment, and provide a real-time feedback
  - Keep the subjects engaged
- Embed an interactive task in the stimuli
  - Show subjects their behavioral performance after each session
  - More complex stimuli features
  - Easy to focus

Stimuli & experimental design: general

- Use **modulated signal** to create a stream of musical notes or vibration pulses
- The carrier frequency changes in the middle of a stream, **forming a pattern**.
- **Spatialize** the sound and vibration (left & right ear/wrist)
- Instruct the subject to **focus on one stream** using a visual cue.
- The subject **responds** with the pattern of the attended stream.

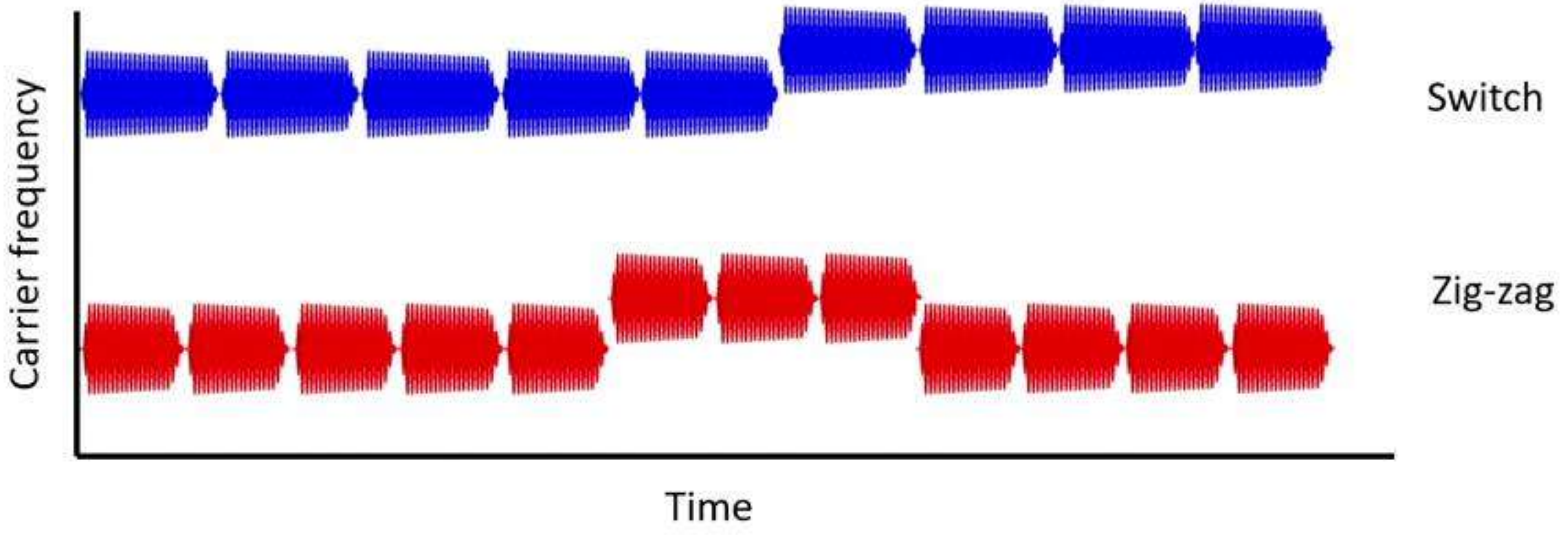
Stimuli: auditory

Channel	Modulation frequency (Hz)	Carrier frequency (Hz)			Length (ms)	Repetition	Pattern
		Low	Standard	High			
Left stream	37	703	740	777	400	9	Up/down /zig-zag
Right stream	44	396	440	484	300	12	



Stimuli: tactile

Channel	Modulation frequency (Hz)	Carrier frequency (Hz)		Length (ms)	Repetition	Pattern
		Standard	Oddball			
Left stream	27	120	210	400	9	Switch / zig-zag
Right stream	17	120	210	300	12	

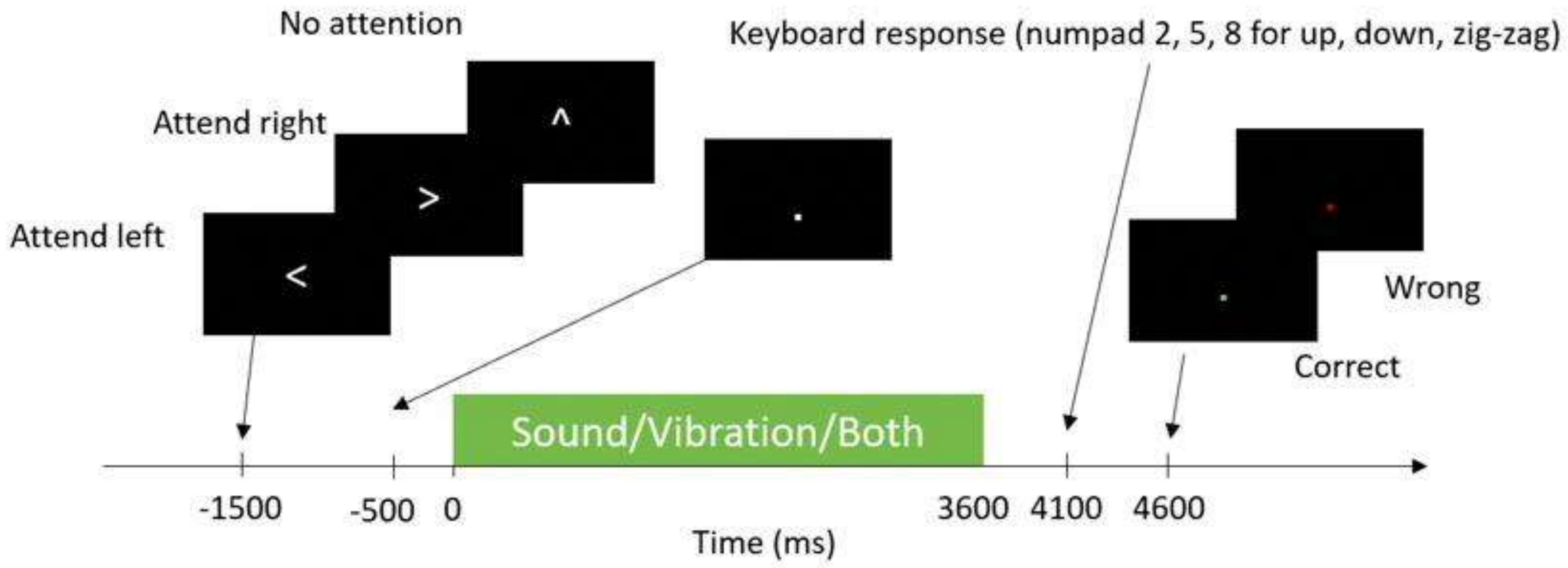


Stimuli: auditory + tactile (mixed)

- Use the same stimuli as in auditory or tactile alone conditions
- The onsets of notes (for auditory) and vibration (for tactile) are synchronized.
- Identify the pattern in the auditory stream (up/down/zig-zag)

Experiment

- 3 modalities (auditory, tactile, mixed)
- 3 conditions per modality (attend left, attend right, no attention)
- 24 trials per condition (randomized)
- ~8 seconds per trial
- ~35 min in total



Possible neural signatures

- Spatial attention
  - Parietal alpha power increase
- Auditory steady-state response
  - Power increased at the modulation frequency of the attended sound
- Somatosensory steady-state response
  - Power increase at the modulation frequency of the attended vibration
- P300 response time-locked to the oddball onset and offset

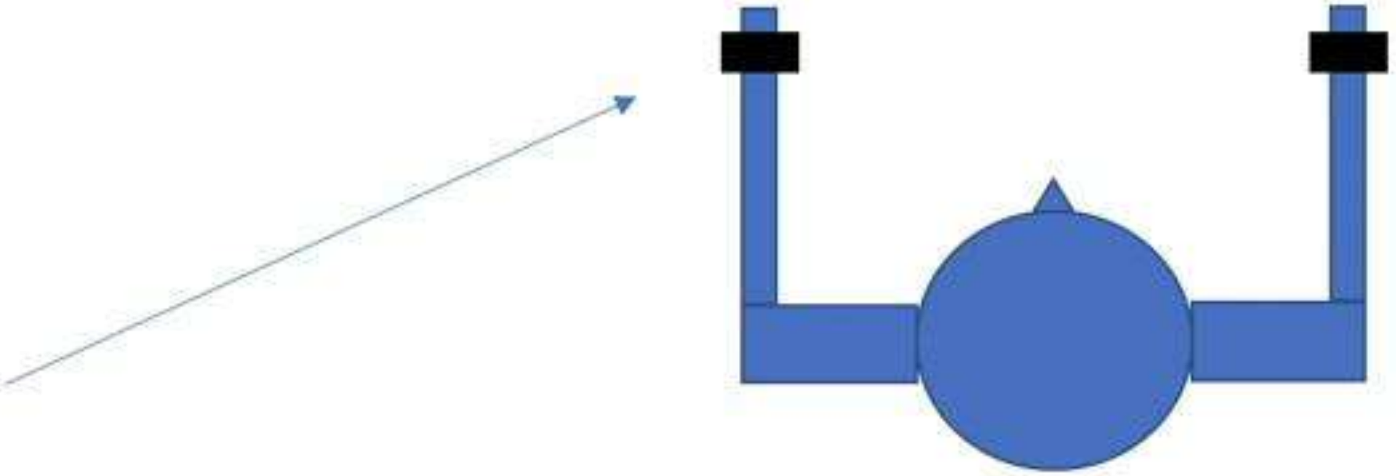
Equipment – EEG systems

- EEG
  - mBrainTrain Smarting
  - 24-channel, gel-based
  - 500Hz

- In-ear EEG
  - Made in-house
  - 2-channel, conductive cloth
  - 250Hz

Equipment – vibrotactile actuator

- Dayton coin-type audio speaker
  - Left and right wrists
  - Free the users' hands for tasks



Data collection

- 12 subjects (3 female, 9 male)
- Age: 32.3 ± 7.4 years old
- 2 with previous BCI experience
- 1 left handed

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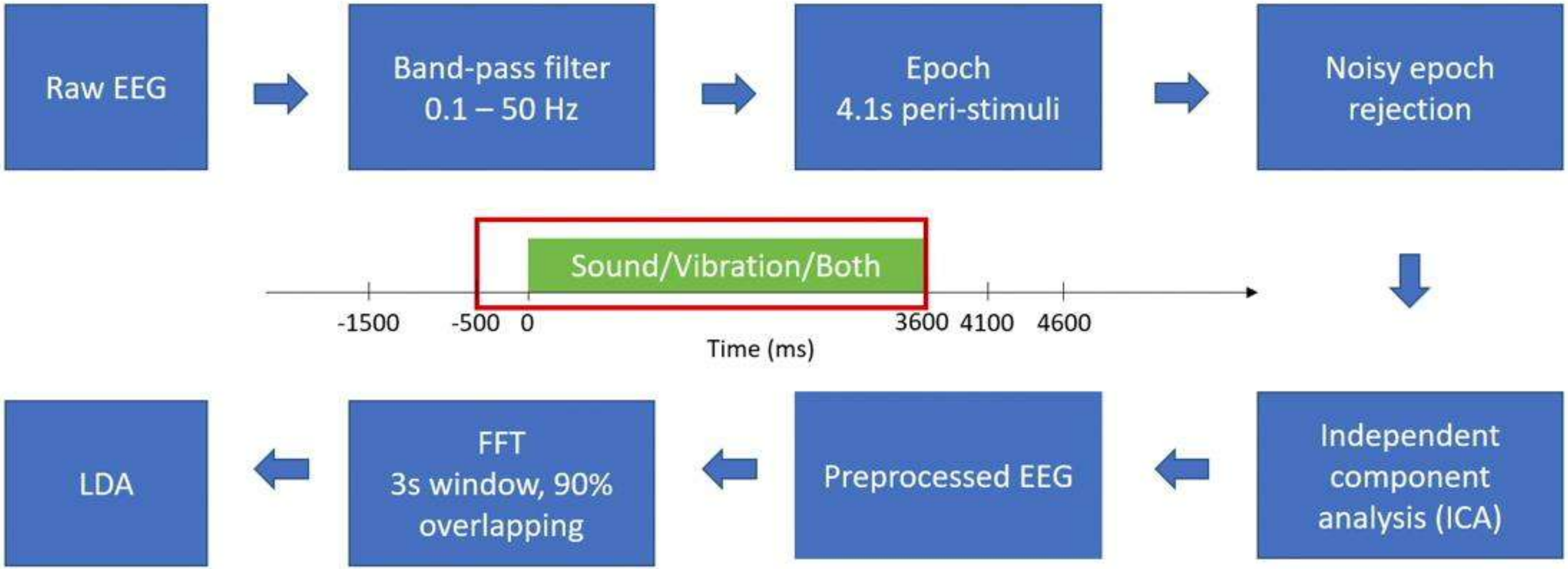
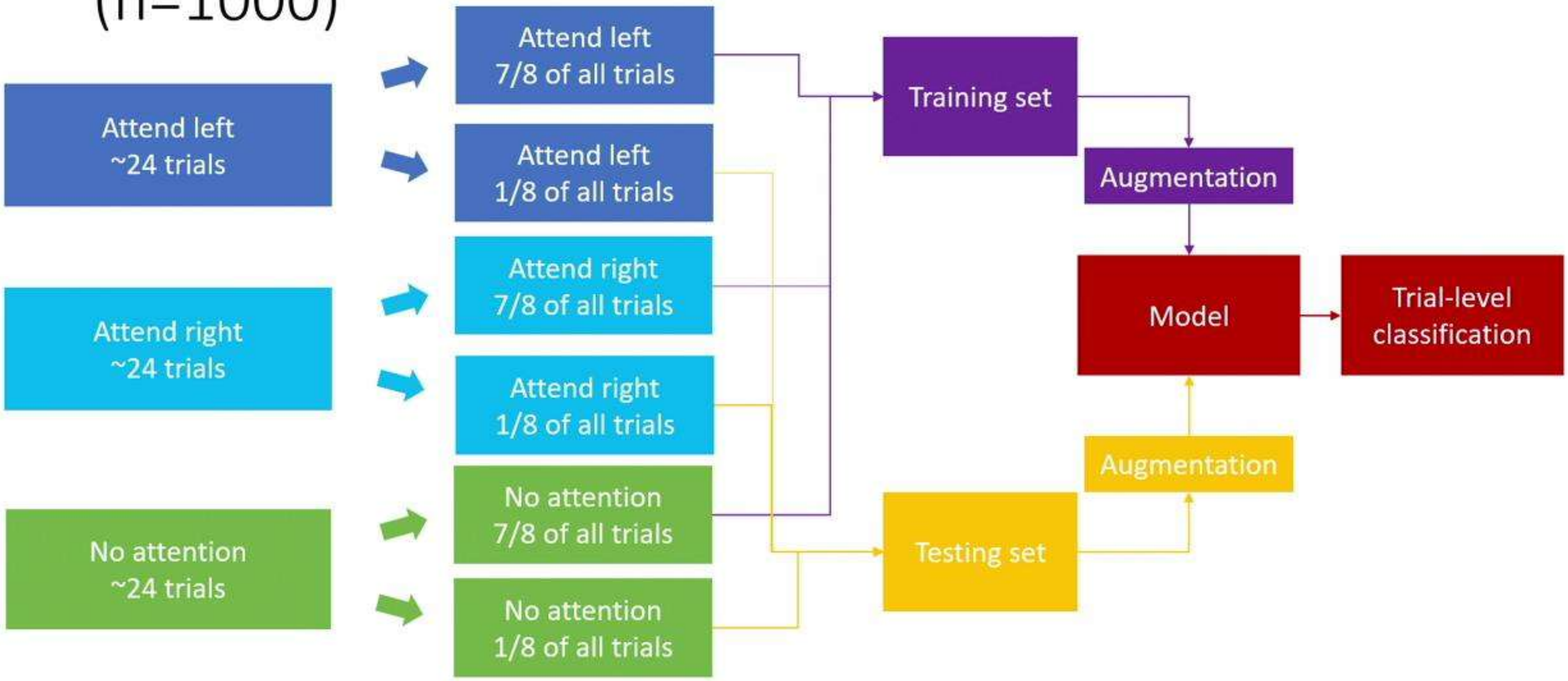
Surface EEG processing and analysis pipeline



3-way classification with 8-fold cross-validation (n=1000)



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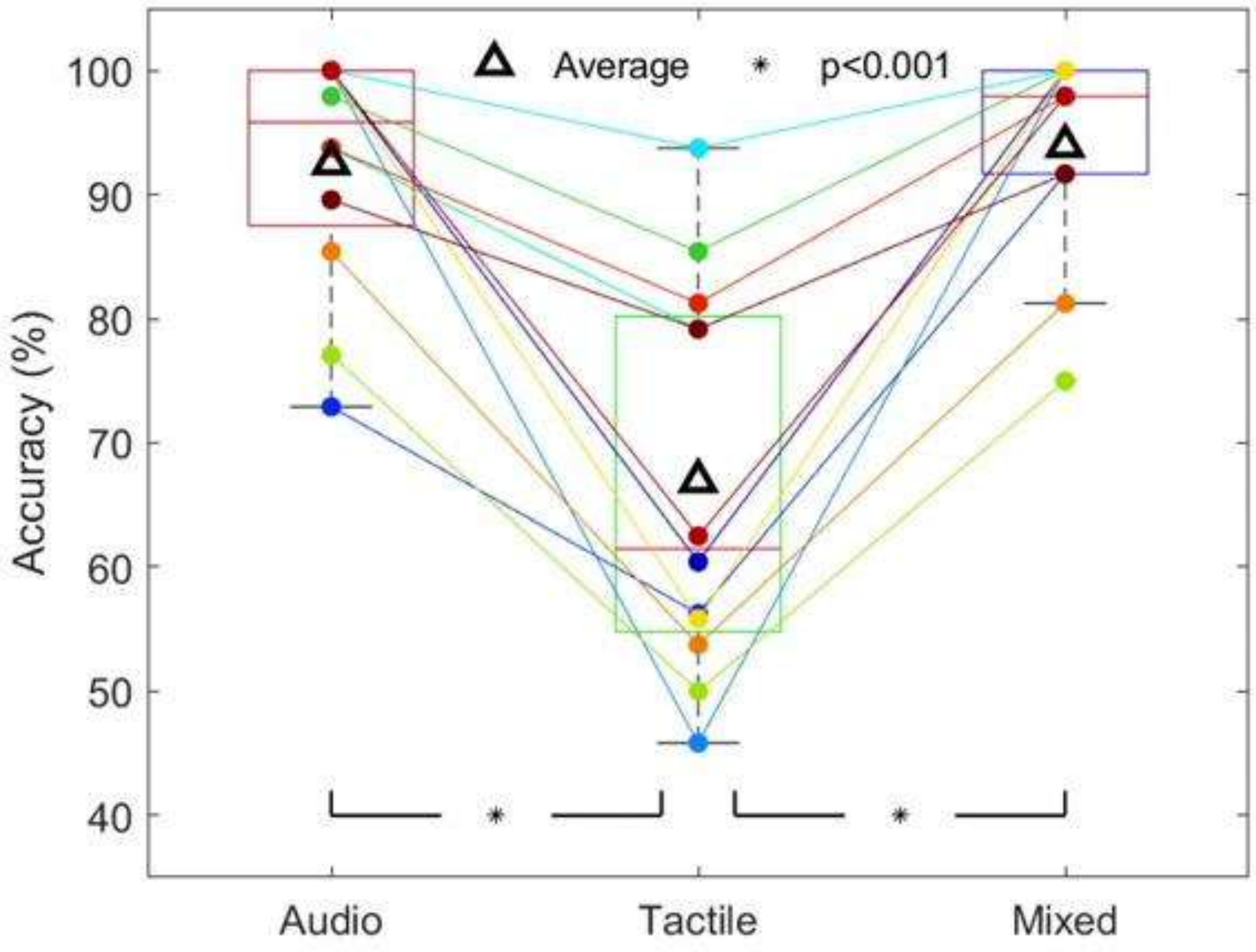
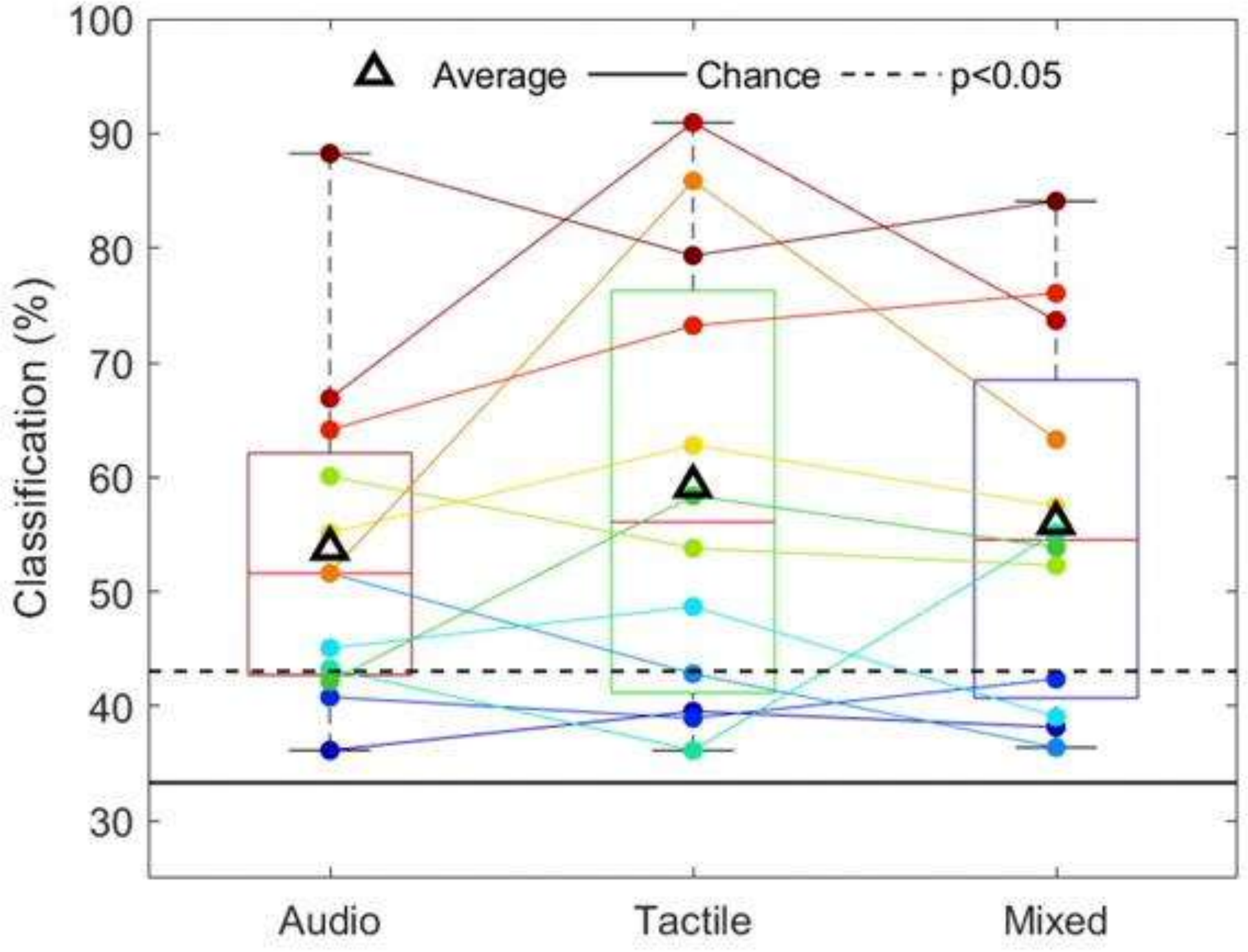
Behavioral performance

- Percent correct of the pattern identification task
- Averaged between attending to left and attending to right tasks
- Each line represents a subject



Surface EEG decoding results by modality

Modality	Mean ± Std (%)	> 33.3% (n)	> 43.1% (n)	ITR (bits/min)
Audio	53.8 ± 13.9	12	9	<1 – 14.27
Tactile	59.2 ± 18.4	12	8	<1 – 16.14
Mixed	56.0 ± 15.1	12	8	<1 – 12.07



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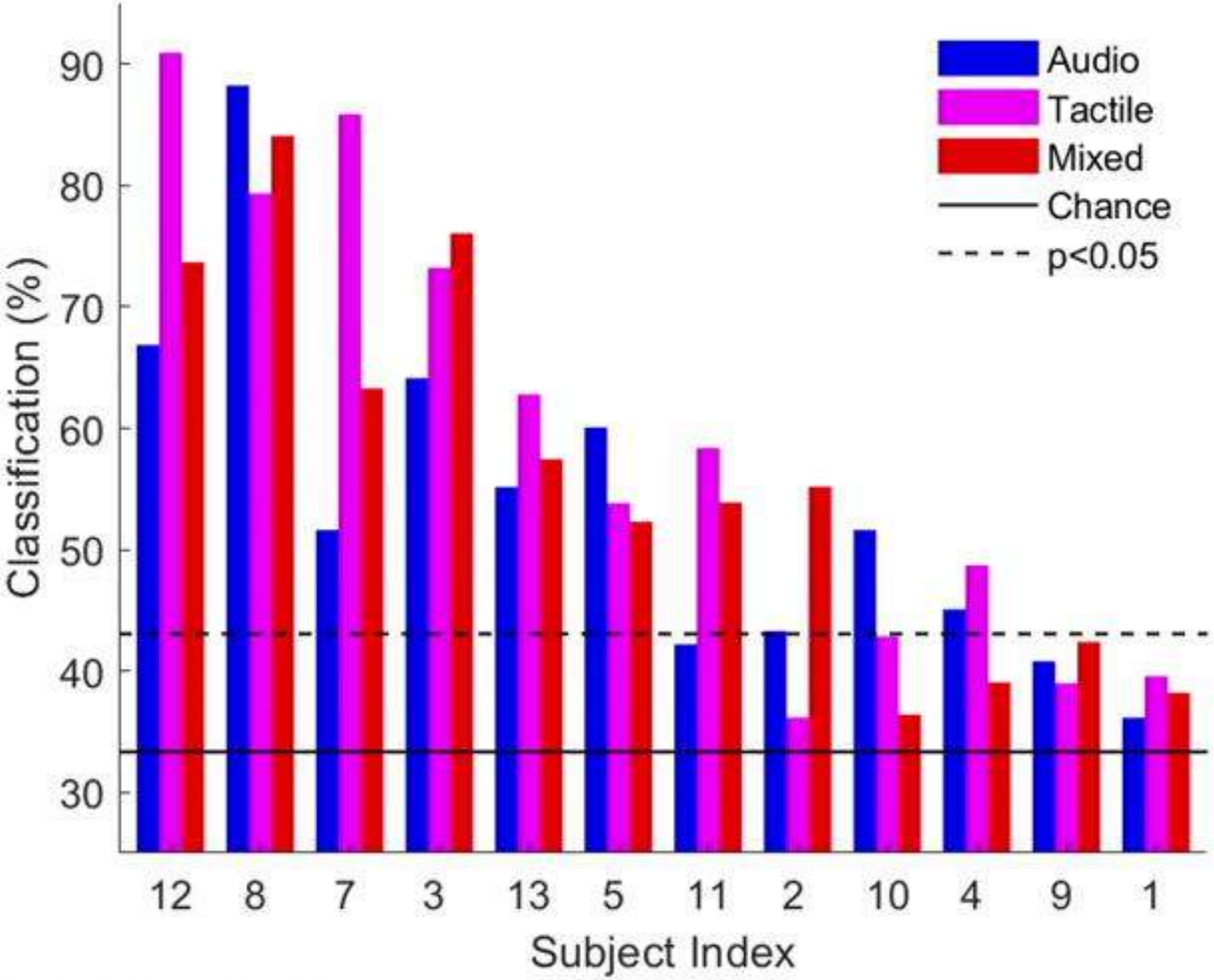
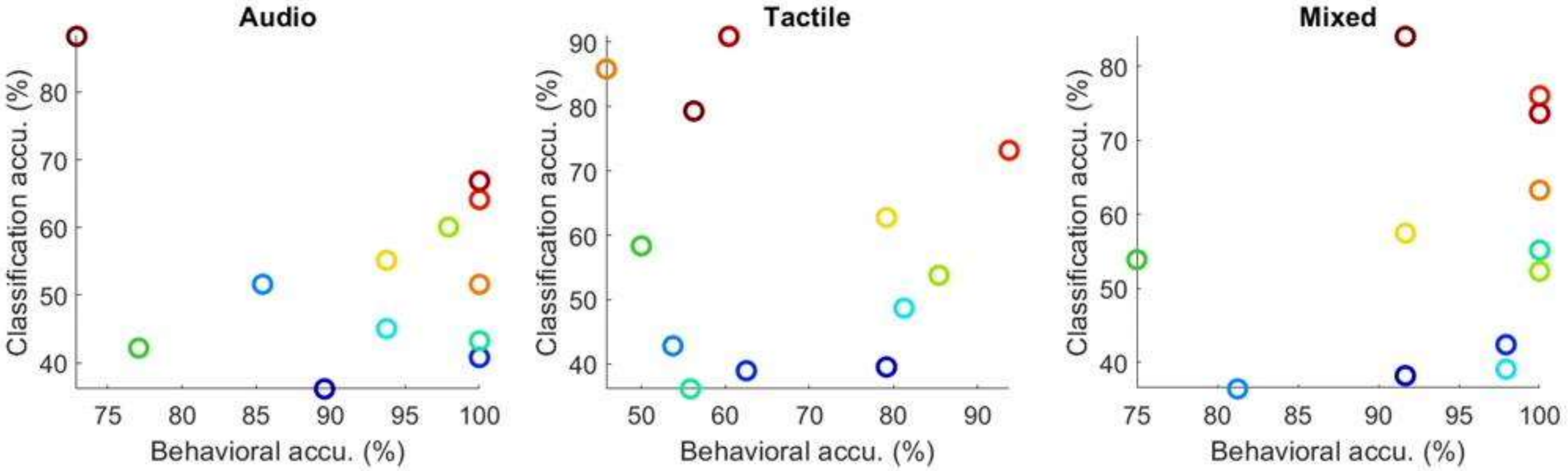


Correlation with behavioral performance



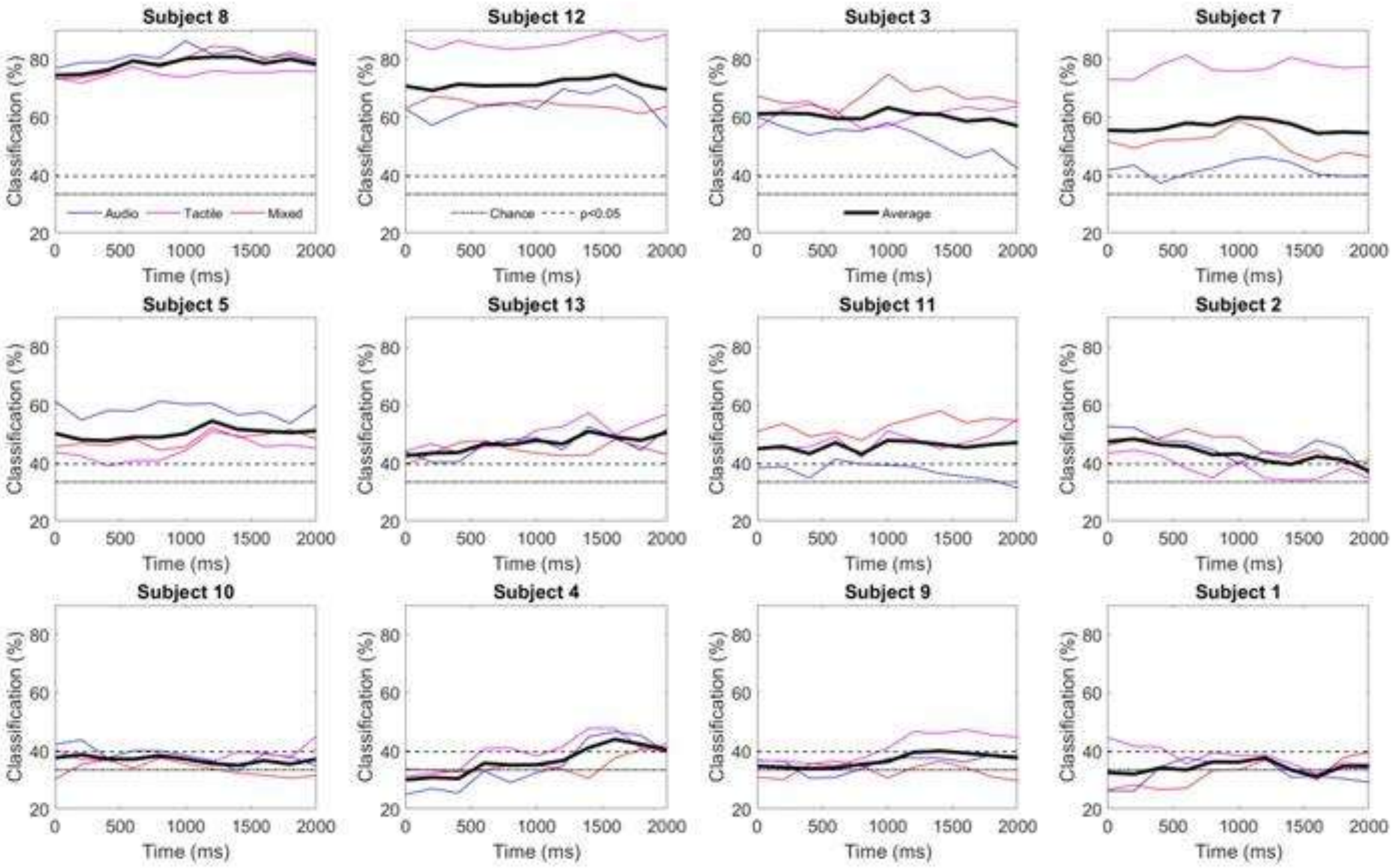
Summary I

- The tactile attention task is more difficult than the auditory and the mixed task.
- The attention decoding results vary across subjects, but are consistent across modalities within each subject.
- The relationship between behavioral accuracy and the classification accuracy seems to be unpredictable.

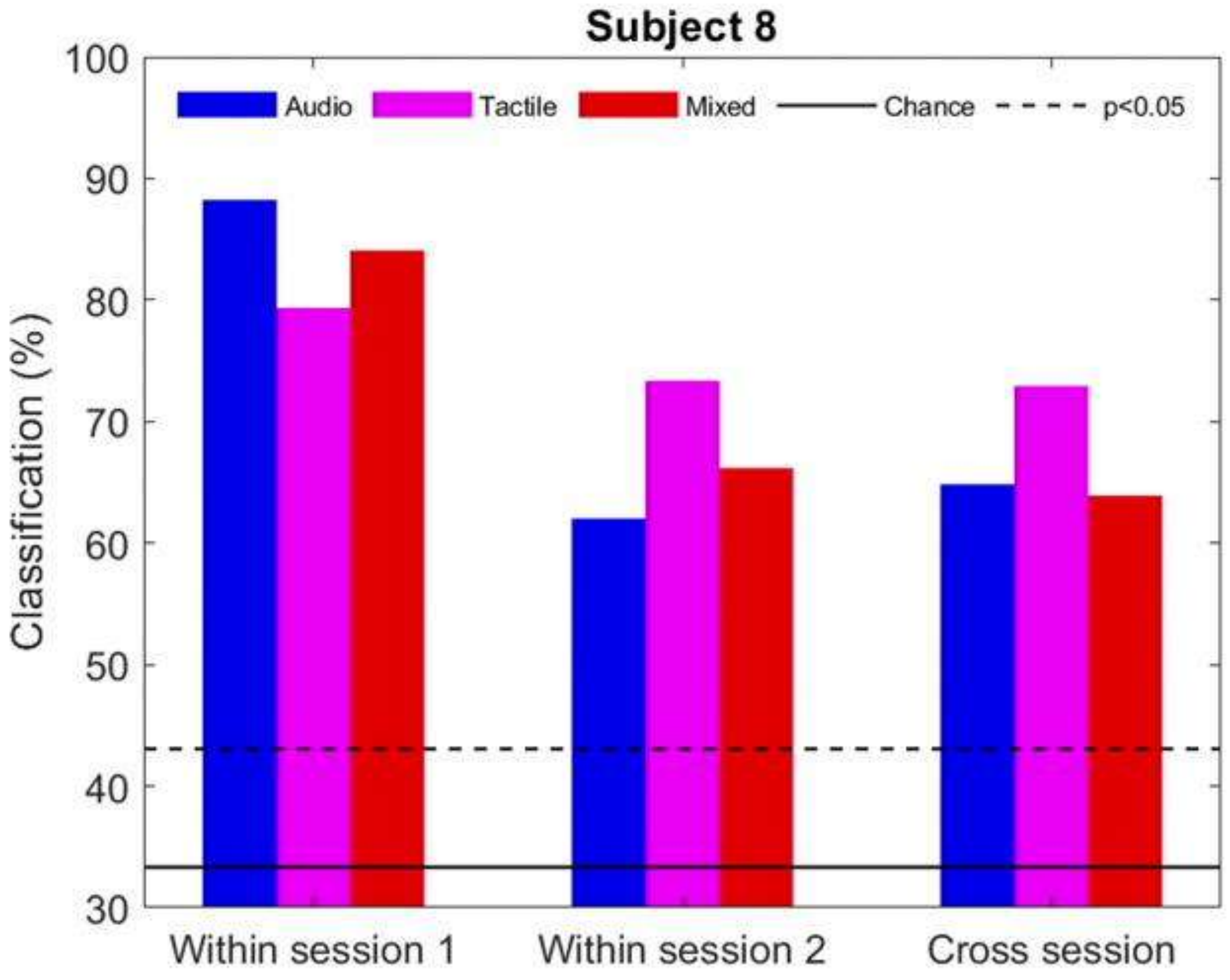
Decoding over time

- 2 second window
- 90% overlap
- Average over all the samples at the same time window

Audio Tactile Mixed
Chance p<0.05 Average



Cross-session validation: a highly classifiable case



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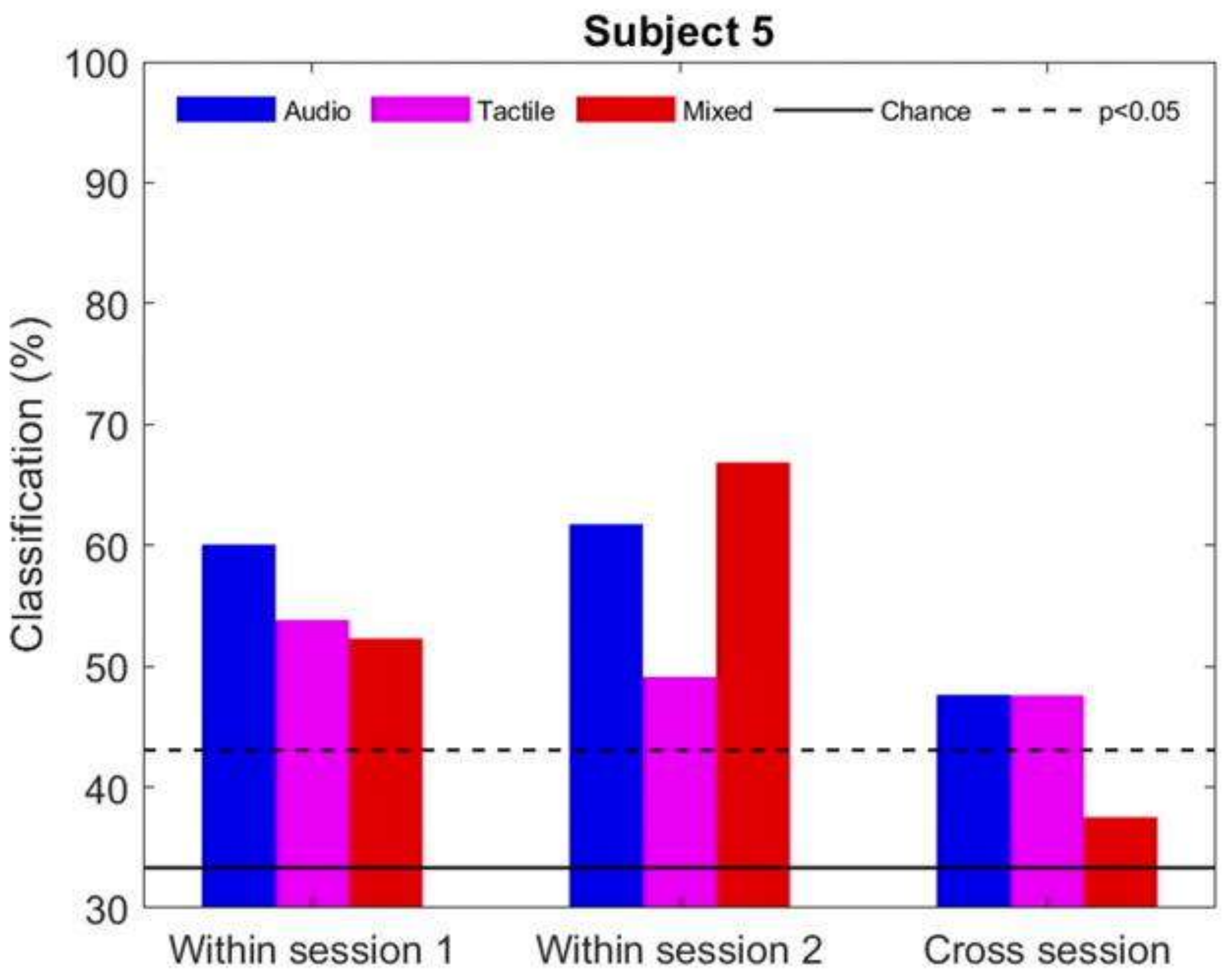
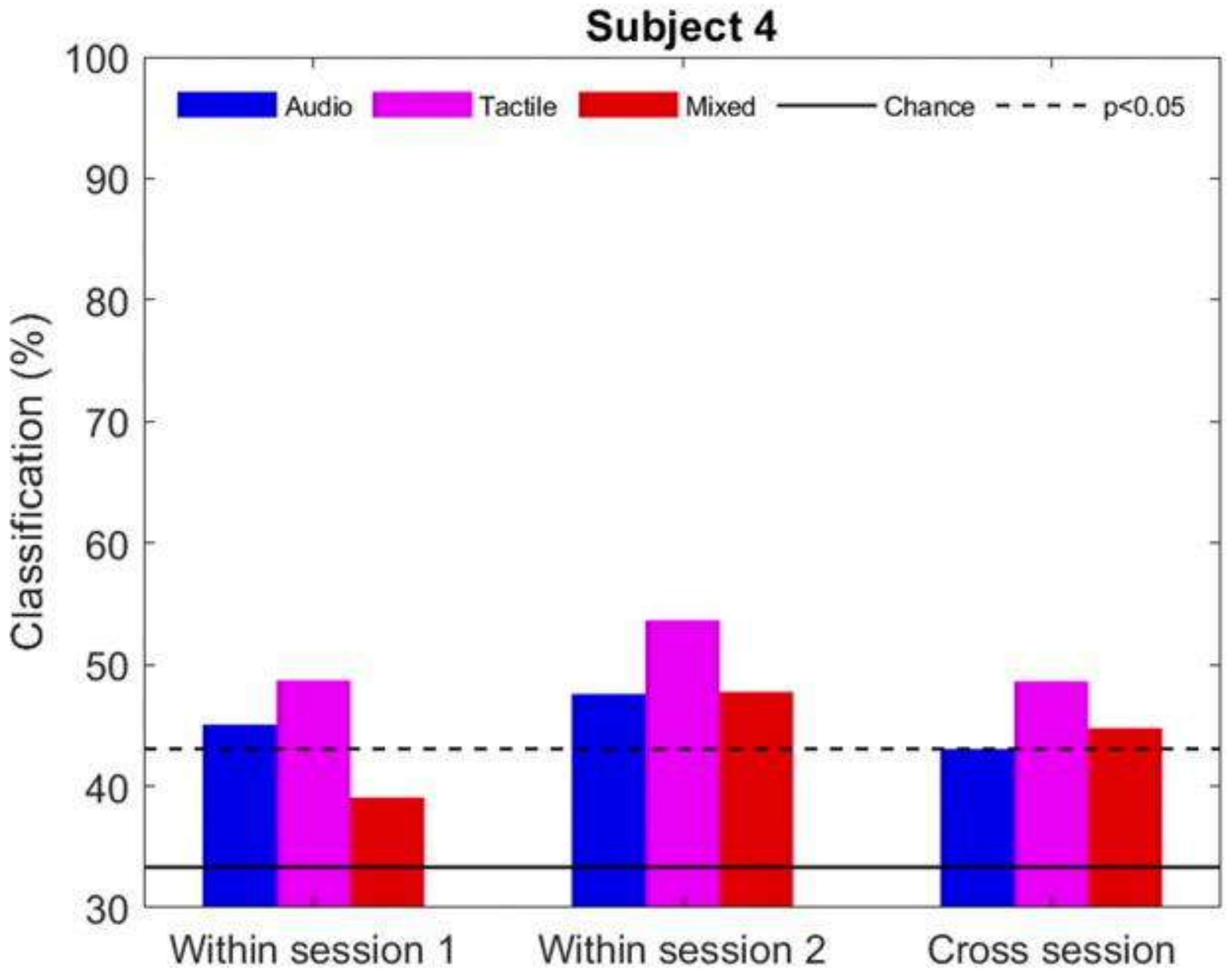
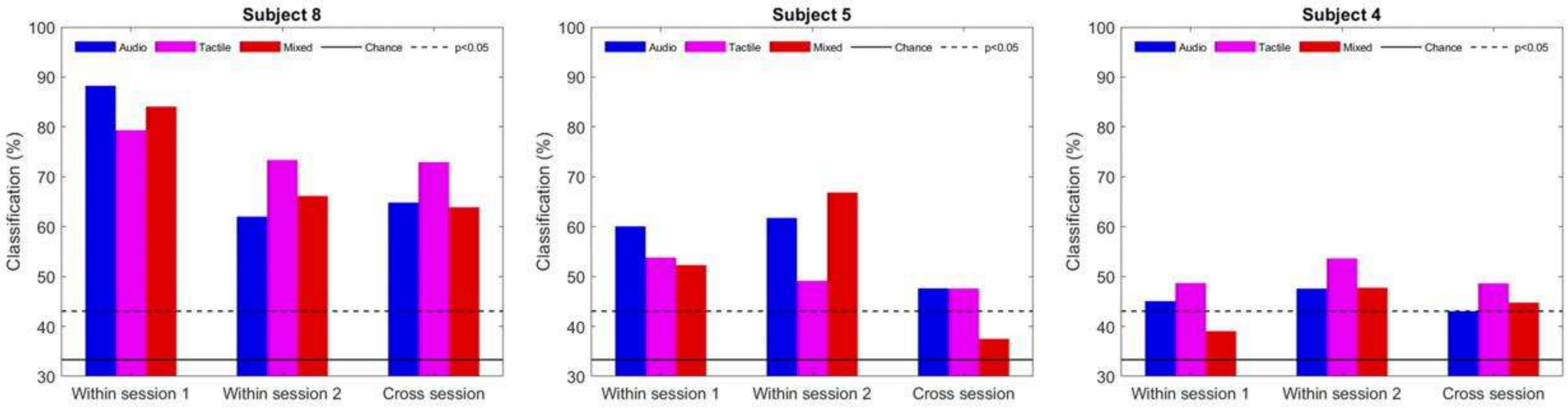


Cross-session validation: a barely classifiable case



Cross-session validation: overall



Summary II

- Decoding accuracy is stable within a trial for most subjects.
  - Sustained attention

- The trained model is robust across multi-day sessions.
  - The model trained today can be used tomorrow to achieve similar results.

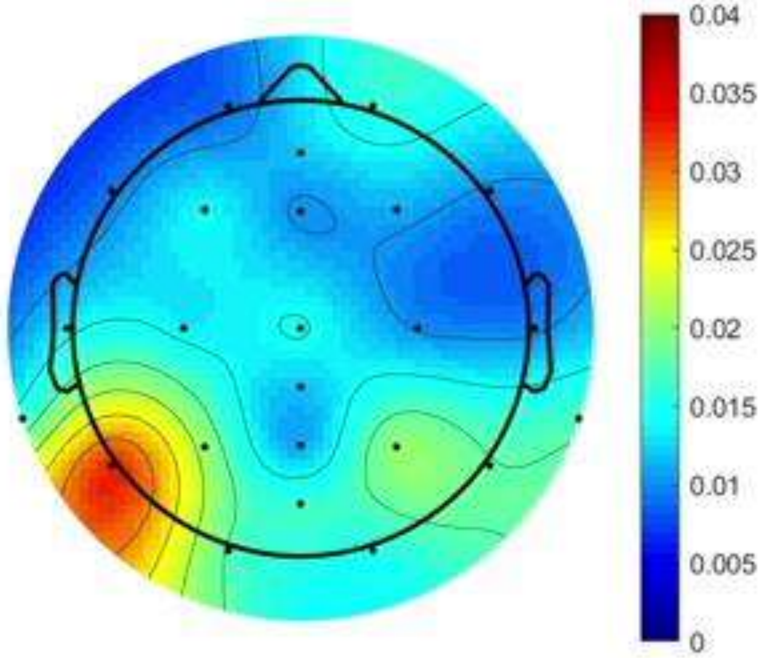
- The performance of the classifier is consistent across multi-day sessions within a subject.

Feature weight

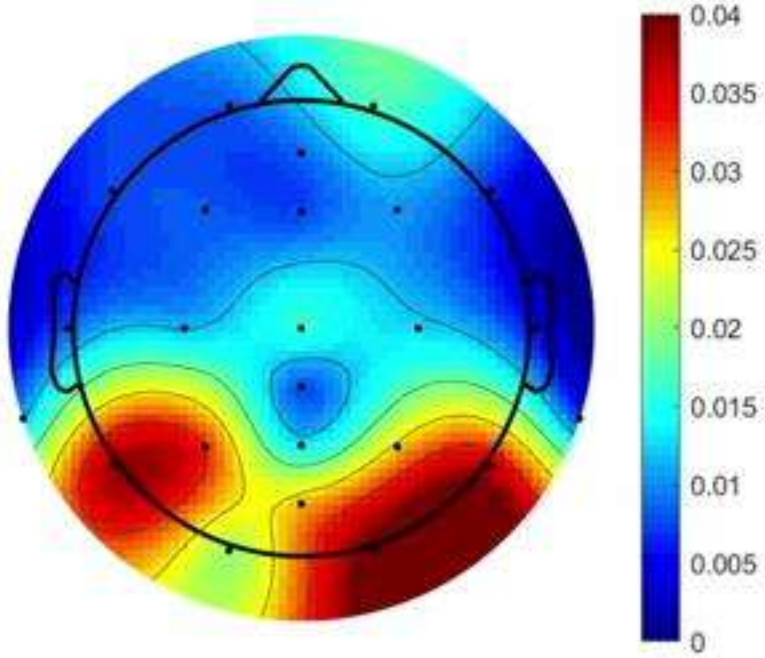
- Neighborhood component analysis (NCA)
  - Feature selection algorithm

Subject 12

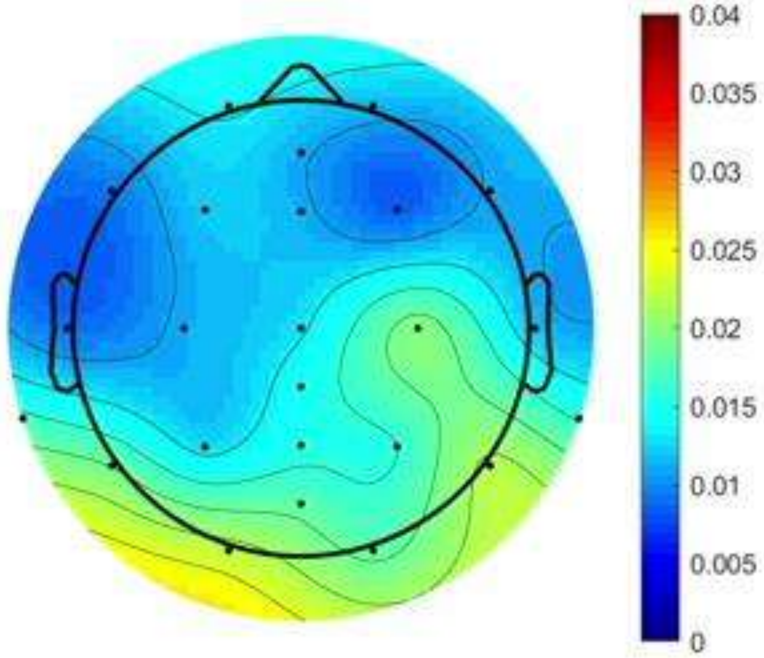
Audio - alpha



Tactile - alpha

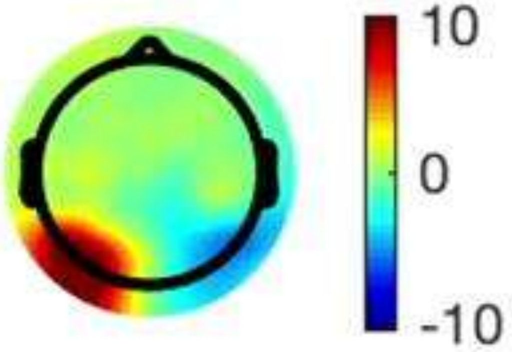


Mixed - alpha



Feature weight

Attend left – Attend right



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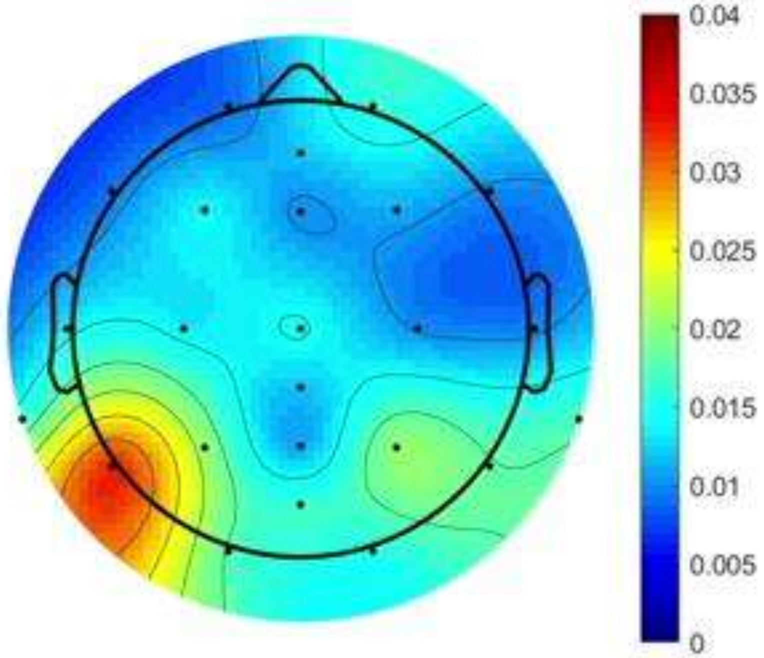
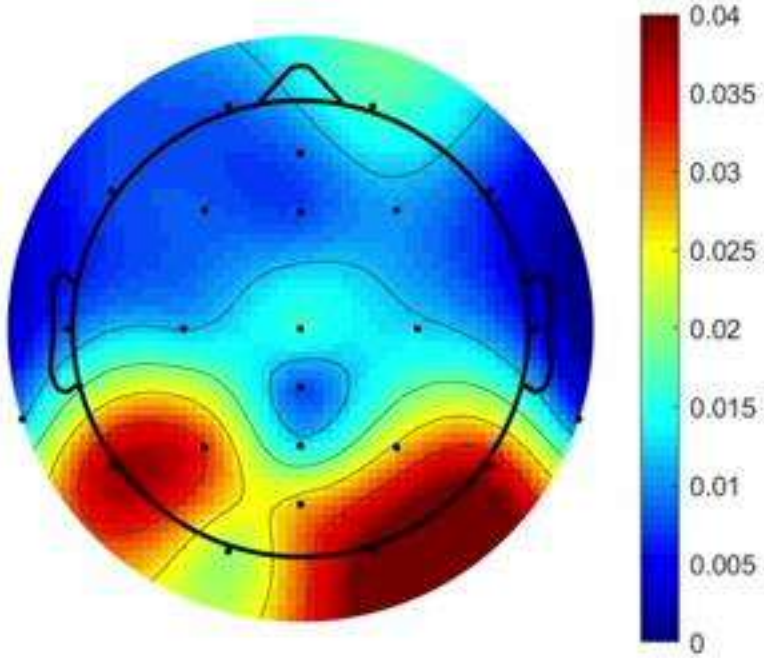
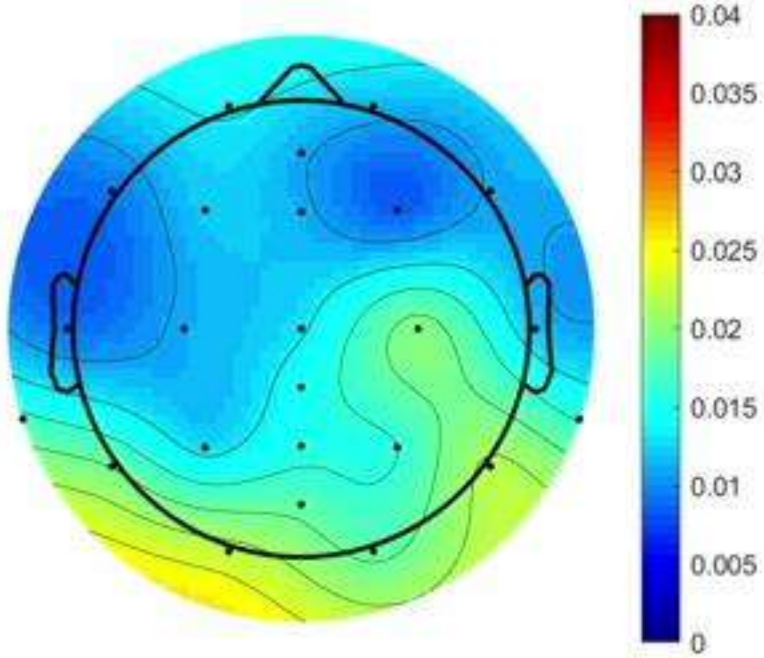


Tactile - alpha



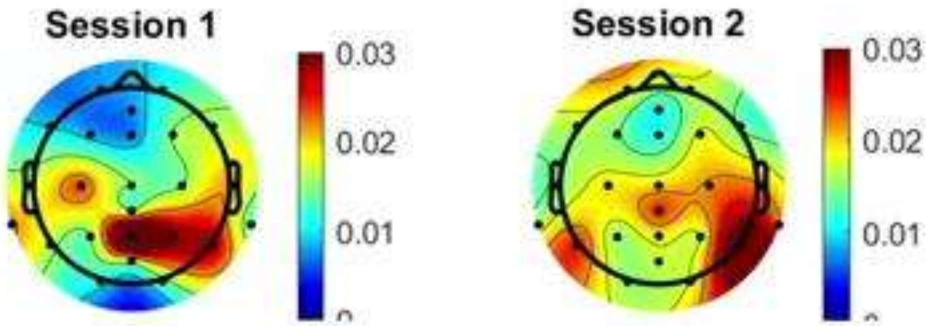
Mixed - alpha



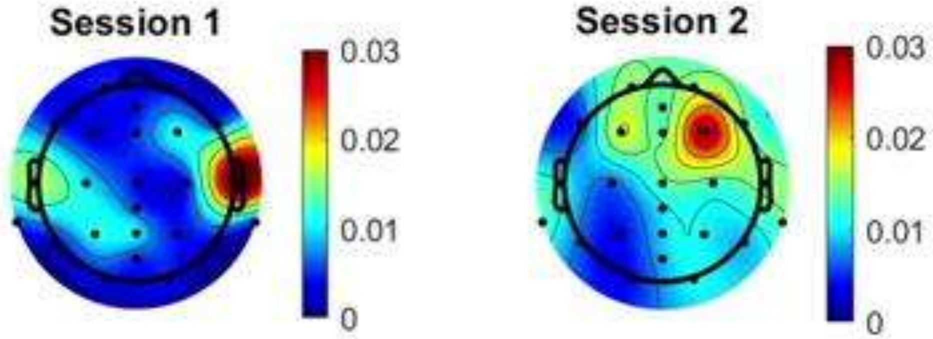
Feature weight consistency between sessions: audio & tactile

Subject 8

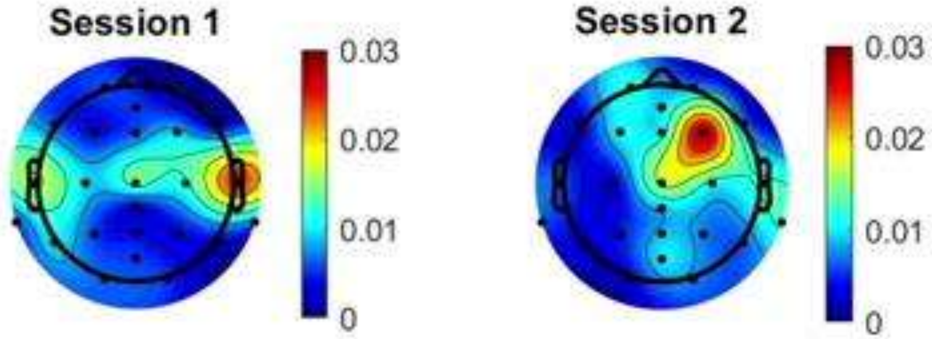
Audio – alpha band



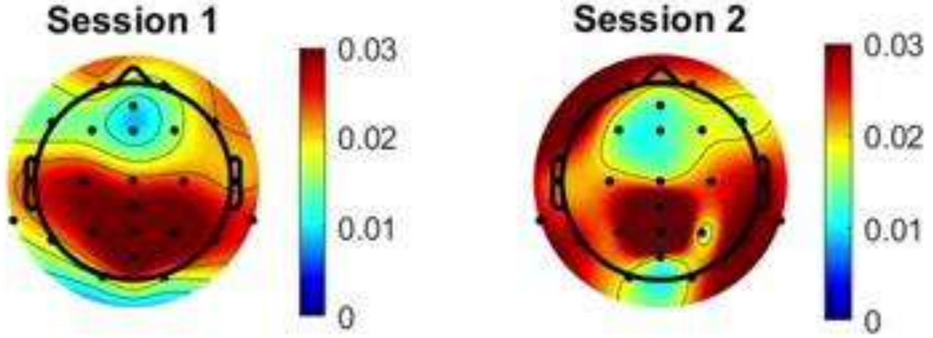
Audio – 37Hz



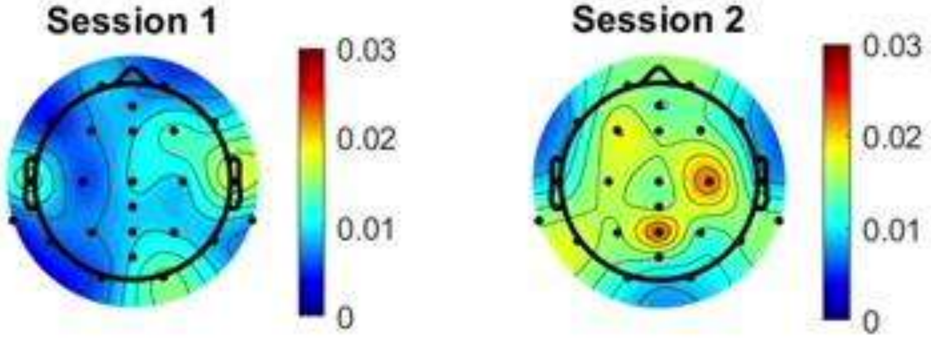
Audio – 44Hz



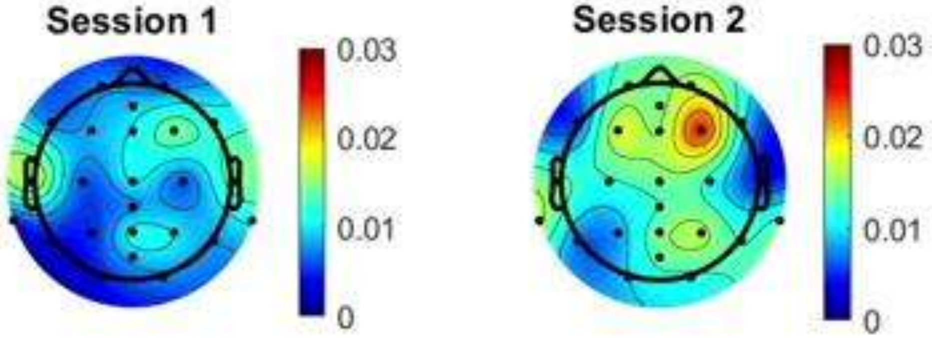
Tactile – alpha band



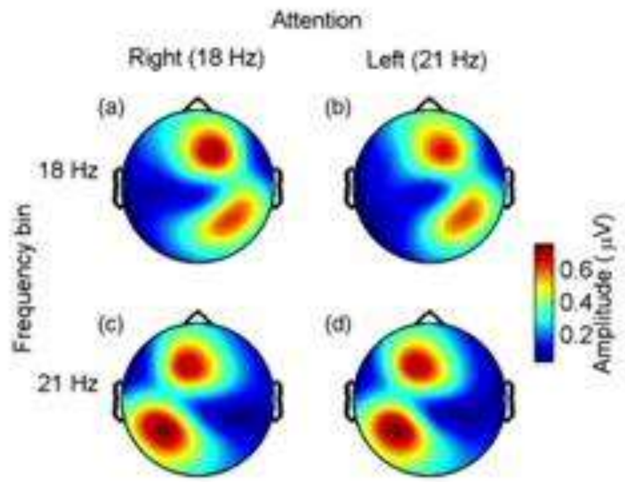
Tactile – 17Hz



Tactile – 27Hz

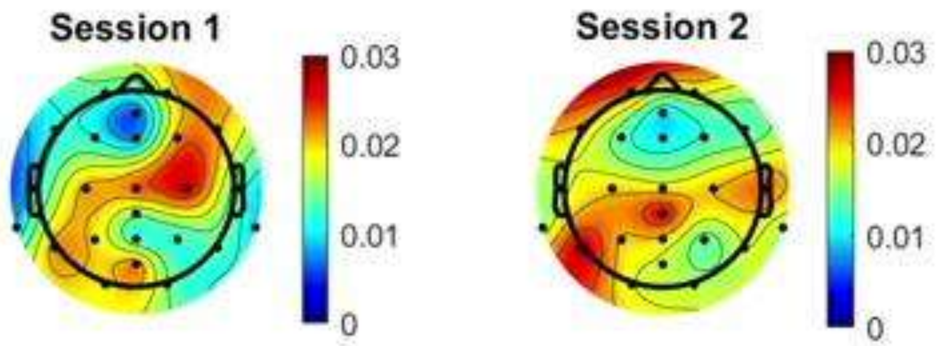


Feature weight consistency between sessions: mixed

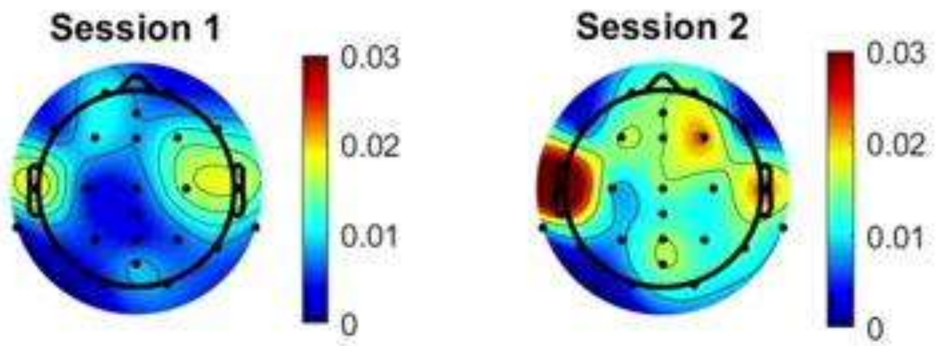


Subject 8

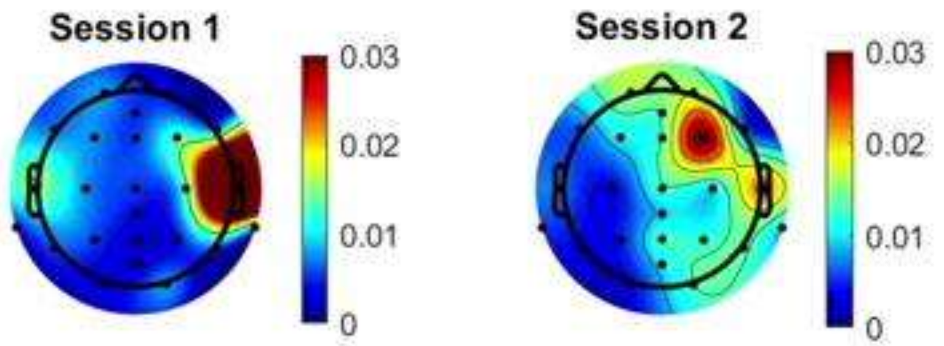
Mixed – alpha band



Mixed – 27Hz



Mixed – 37Hz

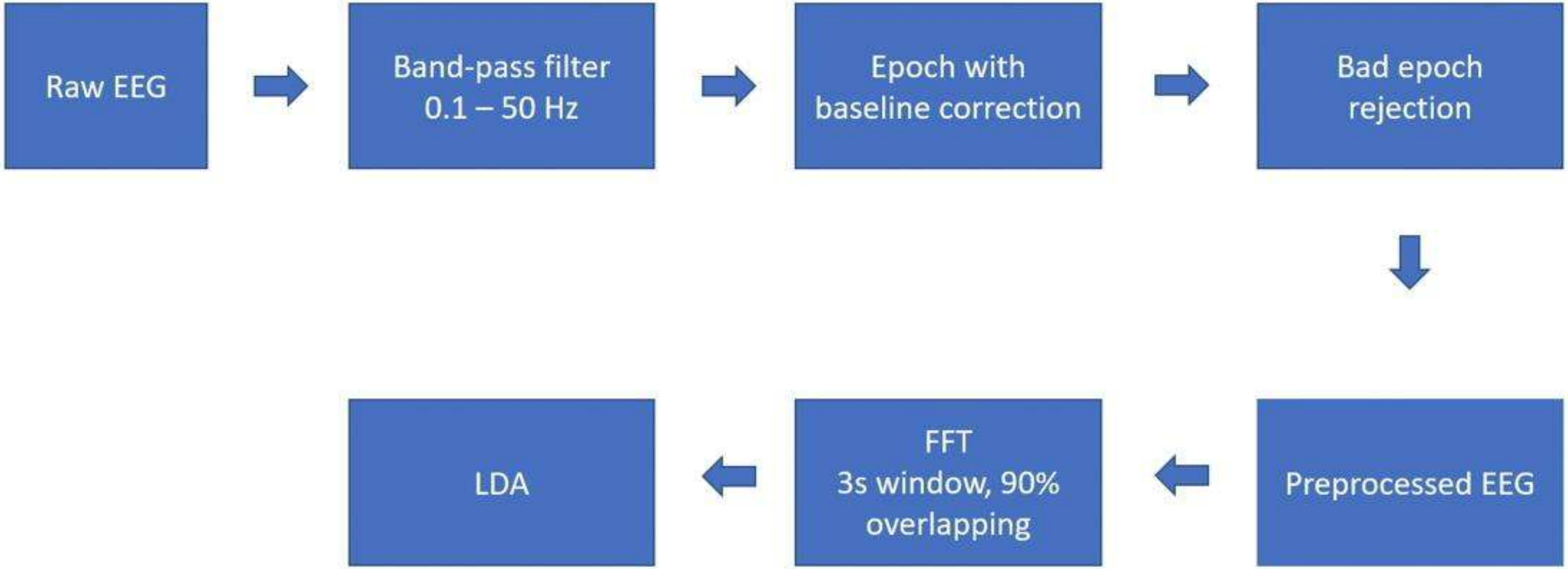


Summary III

- The trained model is decoding attention based on some neurologically relevant features.

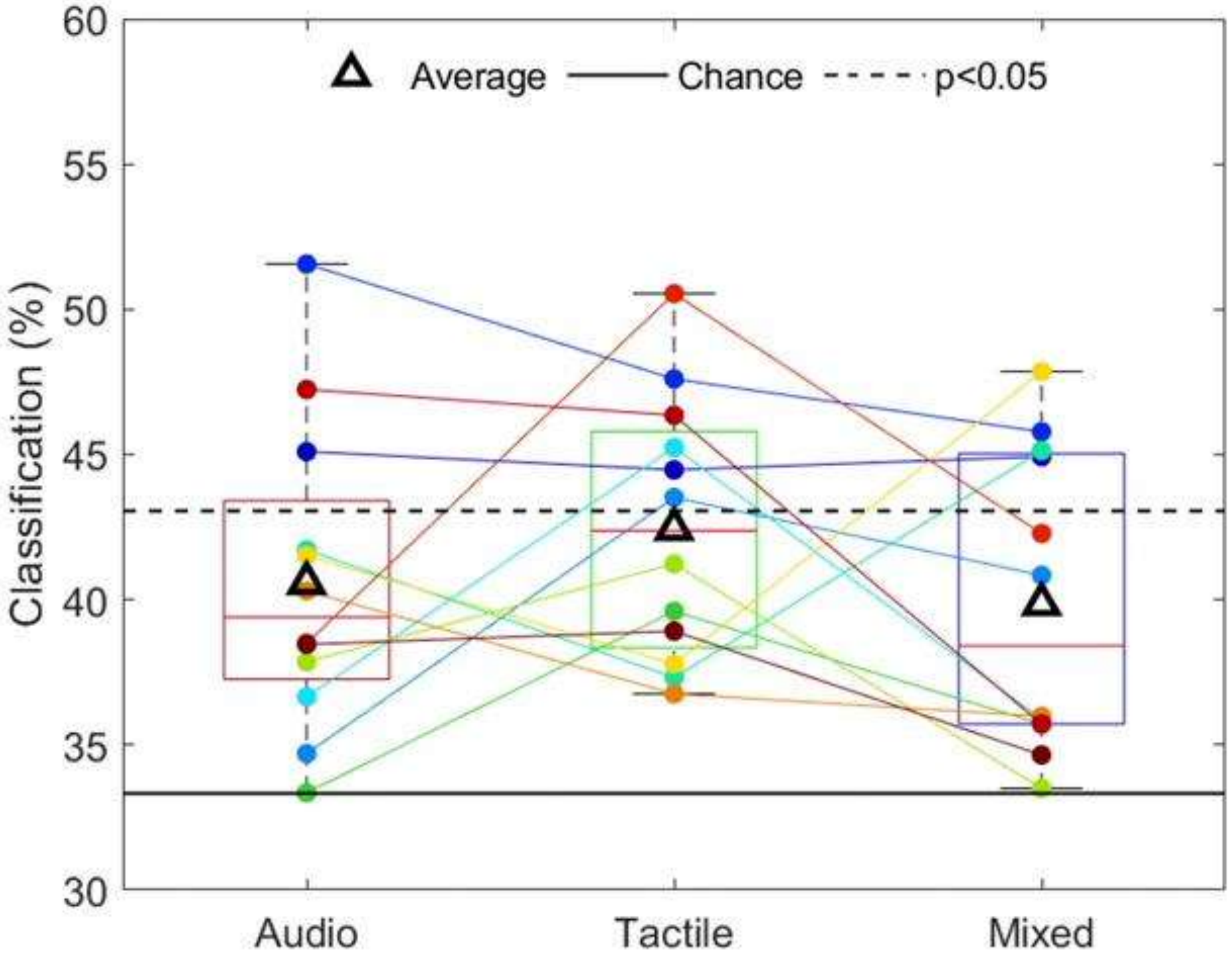
- The feature weights are similar across multi-day sessions within individual subjects.

In-ear EEG processing and analysis pipeline

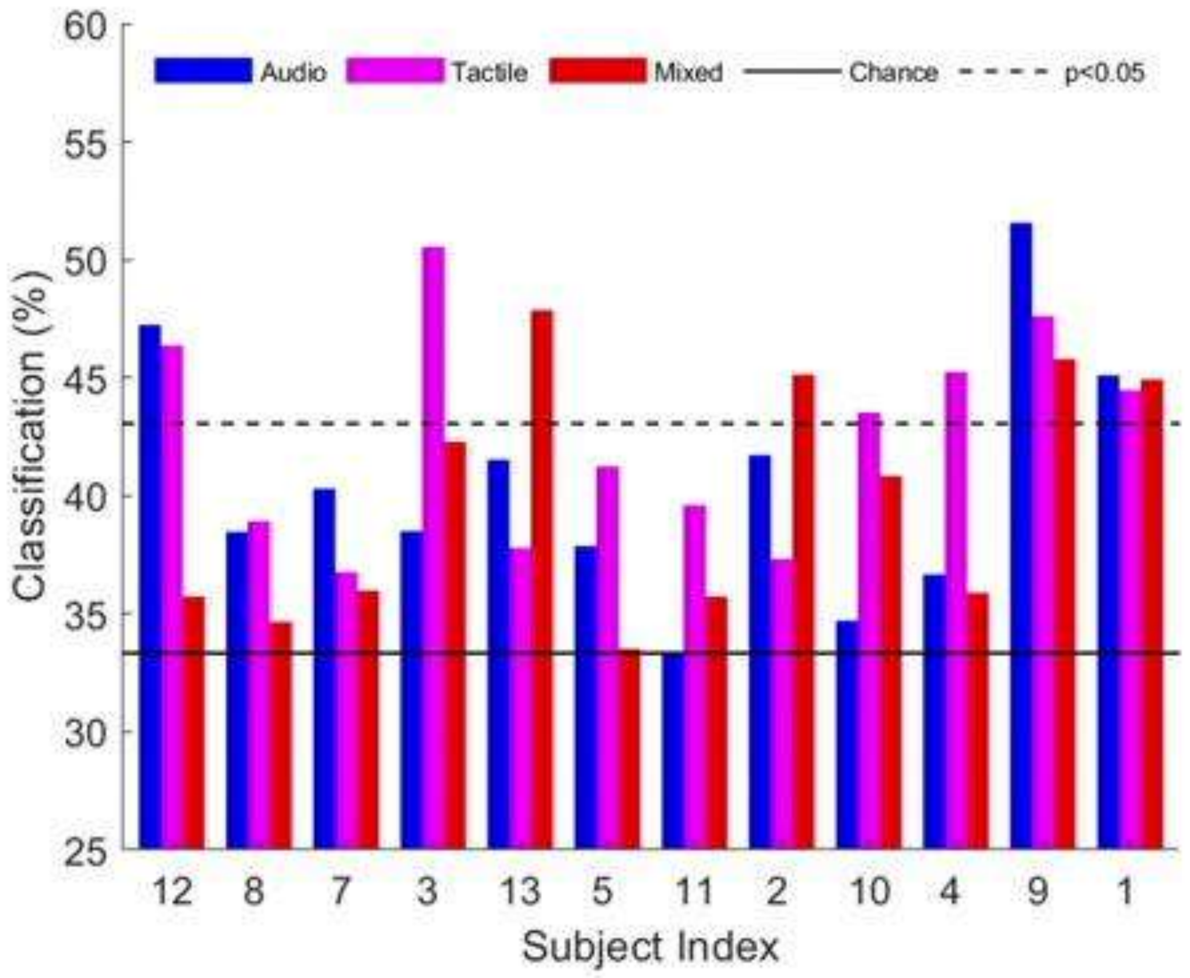


In-ear EEG decoding results by modality

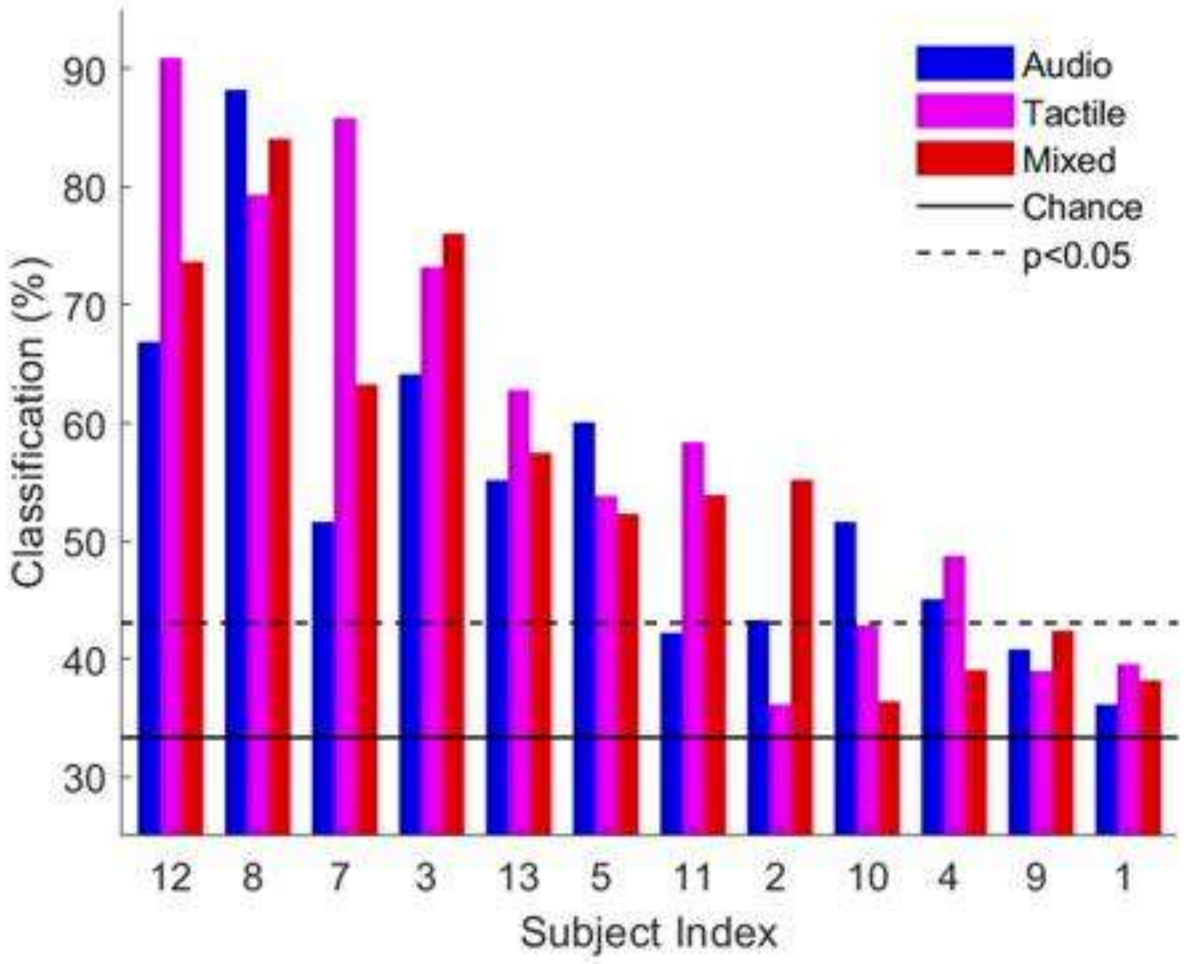
- LDA, 3-way classification
- 1000 cross-validation



In-ear EEG decoding results by subject

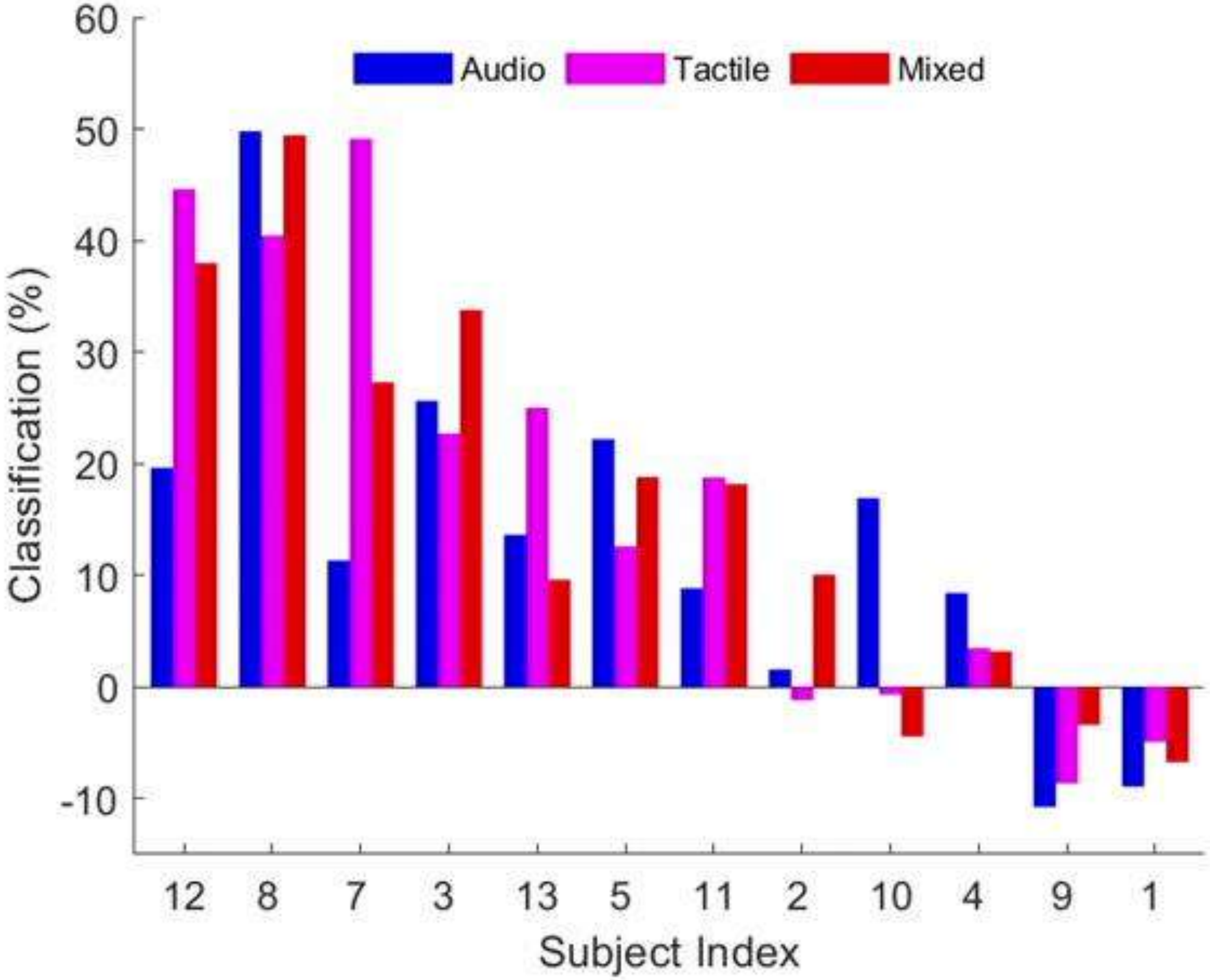


In-ear EEG



Surface EEG

Difference between surface and in-ear EEG decoding accuracy by subject



Summary IV

- The classification accuracy of in-ear EEG is generally lower than that of surface EEG.
- The classification accuracy of in-ear EEG seem to be negatively correlated with the accuracy of surface EEG across subjects.
  - Might be explained by the neural anatomy of individual subjects

Agenda

- Introduction
  - Electroencephalography (EEG)
  - Brain-computer interface (BCI)
- Research objectives & literature review
- Experiment & equipment
- Signal processing and data analysis
- Results
- Conclusions & future works

Conclusions

- Integrate auditory and tactile stimuli into an interactive task-based paradigm is a feasible way to build a functional BCI system.

- The performance of the proposed BCI system
  - outperforms previous studies using steady stimuli.
  - is comparable across sensory modalities.
  - varies across subjects.
  - is robust over time within each subject.

- In-ear EEG may be able to capture some information missed by the surface EEG, which has the potential to be used in a customized BCI system.

Future works

- Feature dimensionality reduction
  - Feature selection
- Use neural network to decode attention
  - Preliminary results show that there is a potential gain in classification accuracy, but the amount of gain varies across subjects.
- Integrate of spatial information into classification
- In-depth analysis on individual differences
- Improve task/game design and stimuli

Acknowledgement

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Special thanks to Lincy Wang

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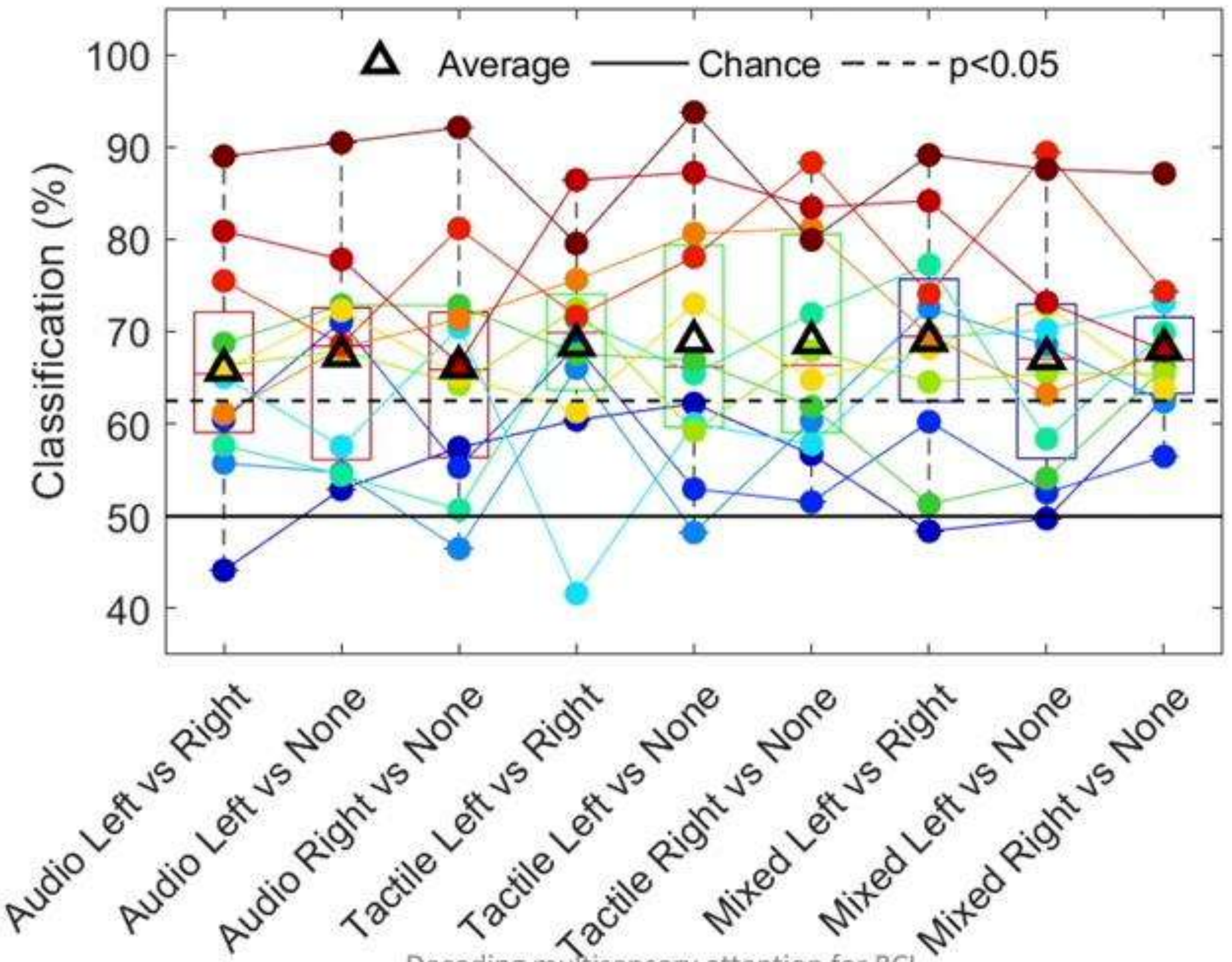
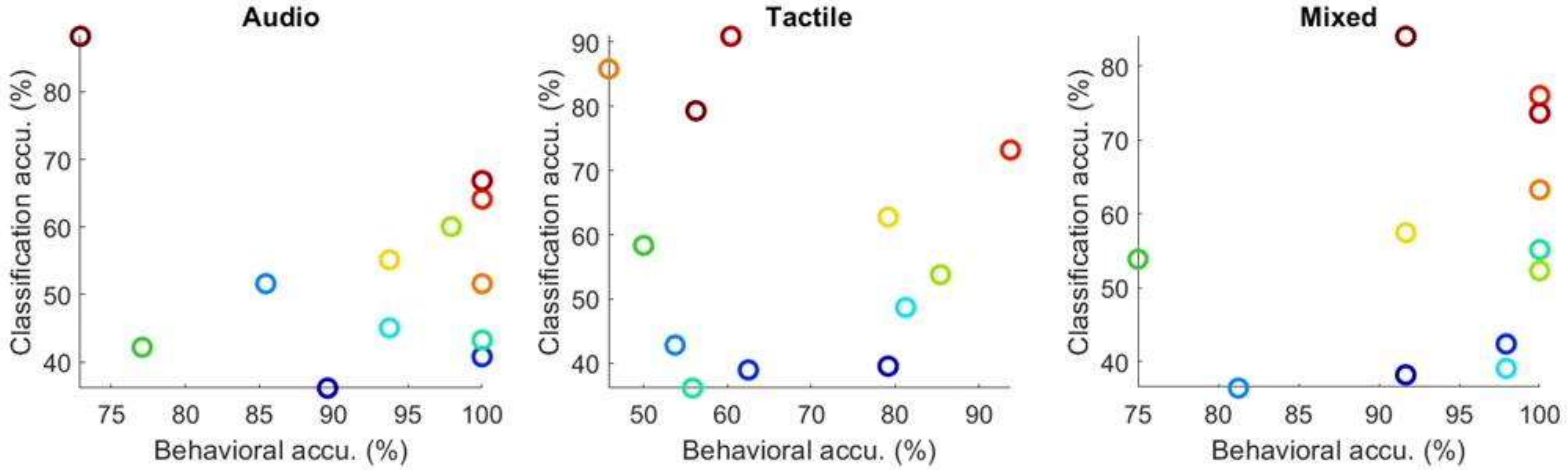
Thank you!

Binary classification – surface EEG

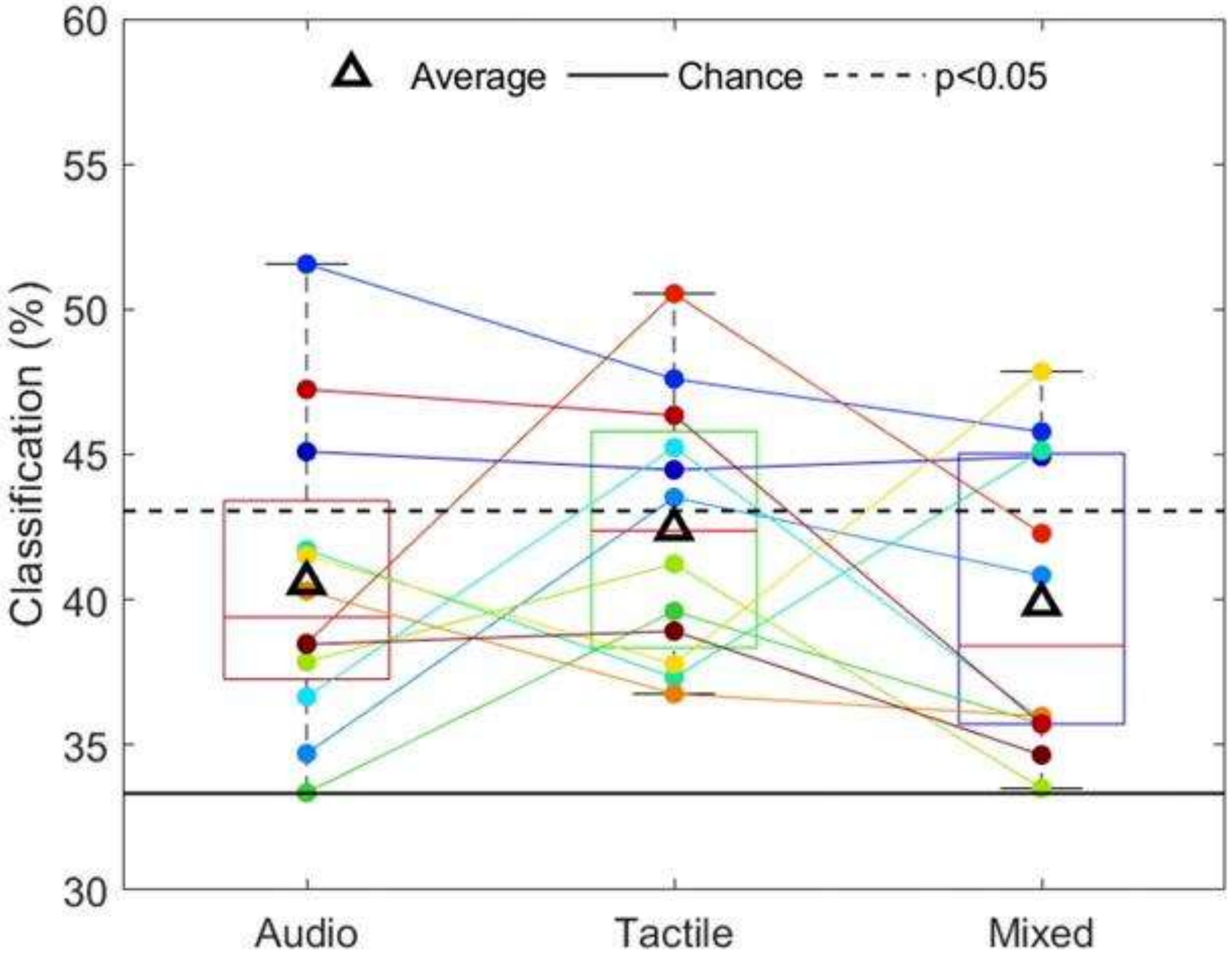


Correlation with behavioral performance



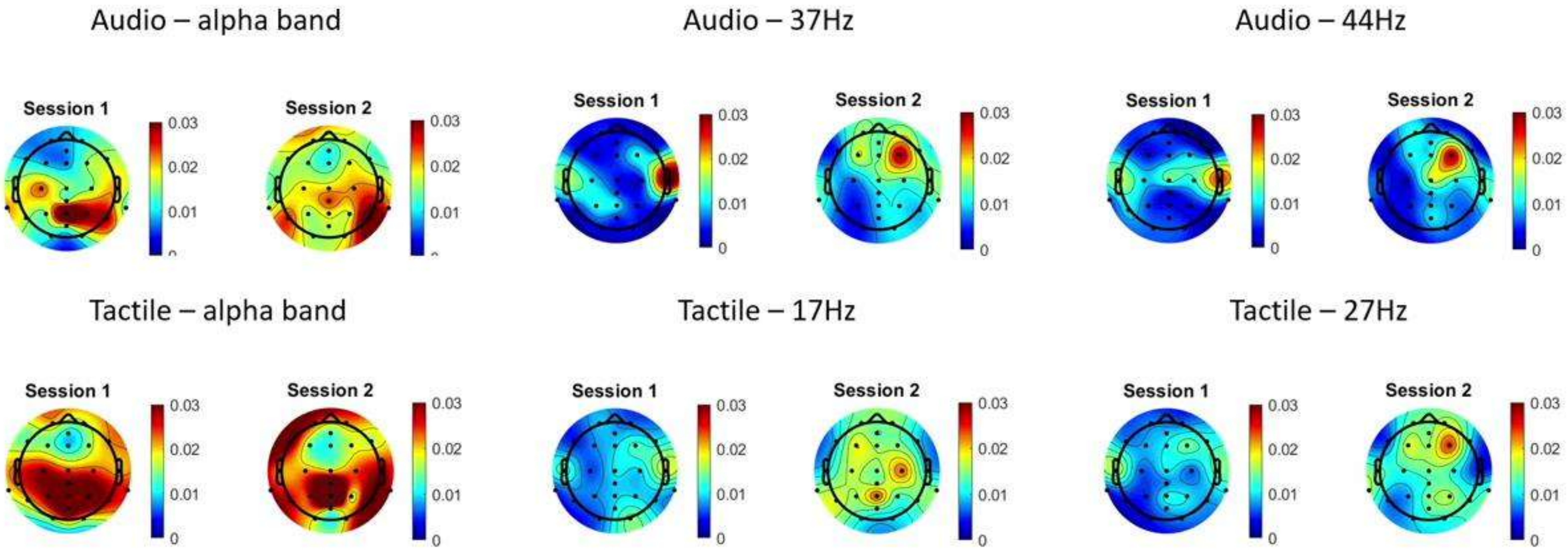
In-ear EEG decoding results by modality

- LDA, 3-way classification
- 1000 cross-validation



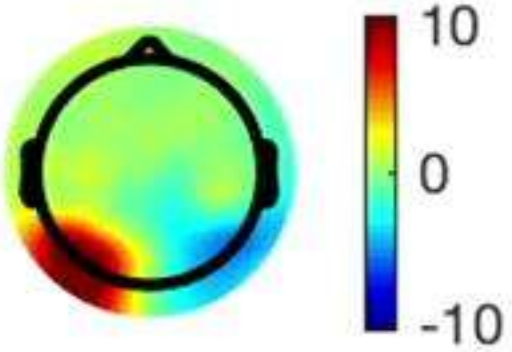
Feature weight consistency between sessions: audio & tactile

Subject 8



Feature weight

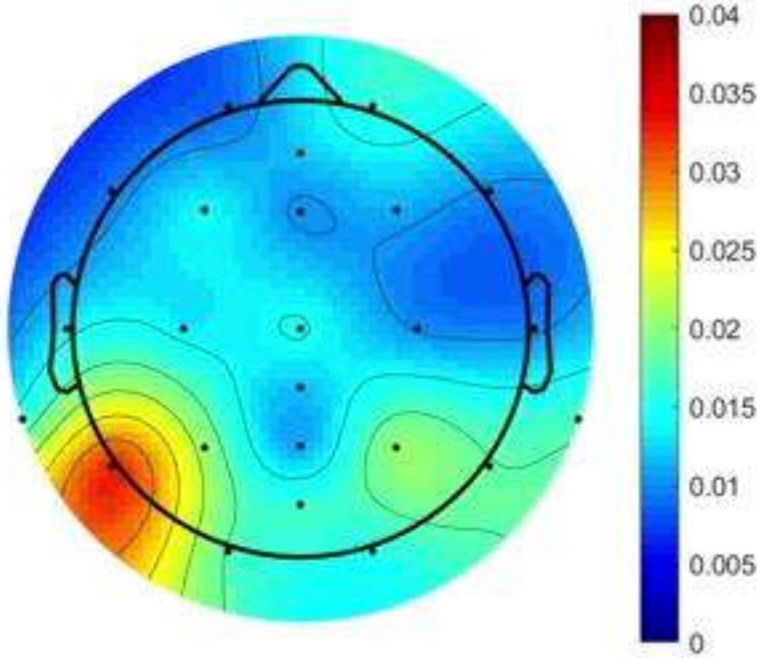
Attend left – Attend right



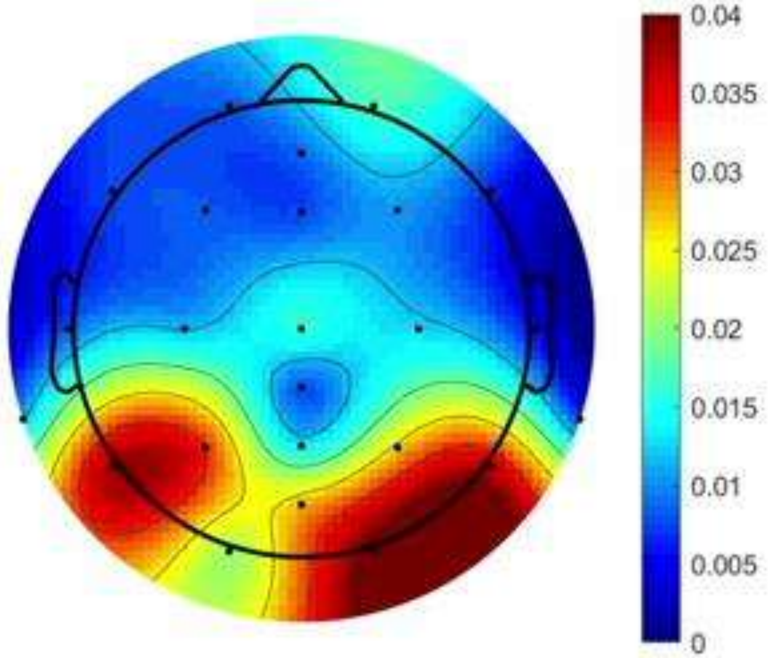
- Neighborhood component analysis (NCA)
  - Feature selection algorithm

Subject 12

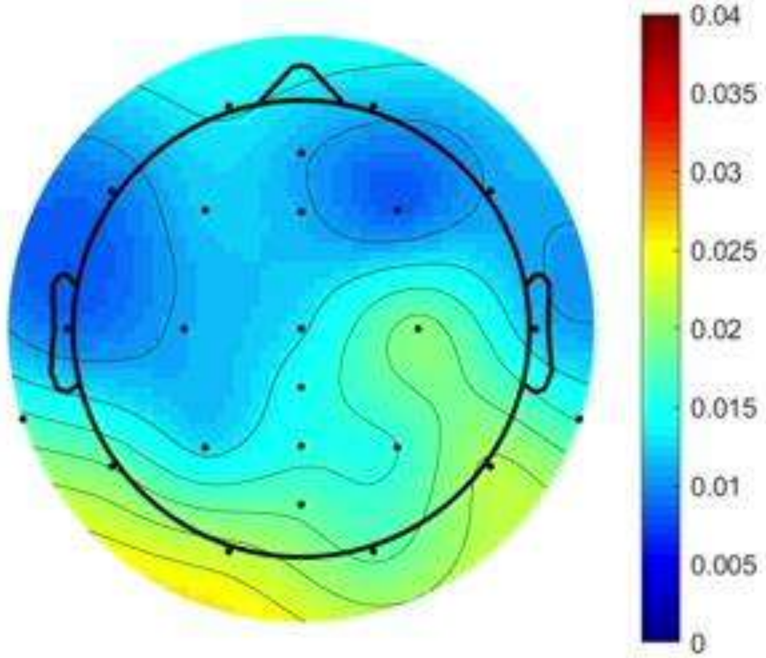
Audio - alpha



Tactile - alpha



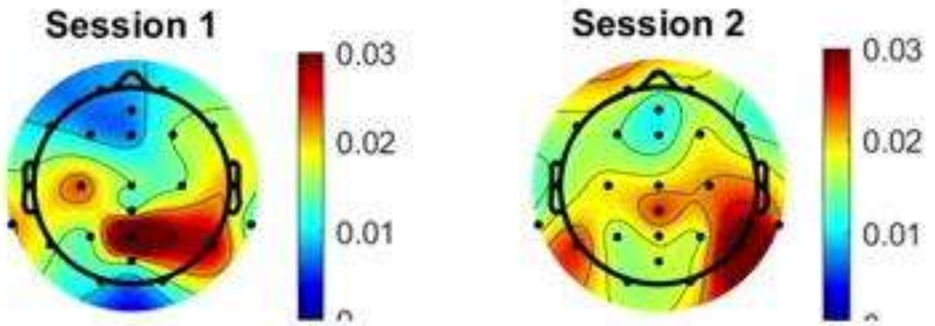
Mixed - alpha



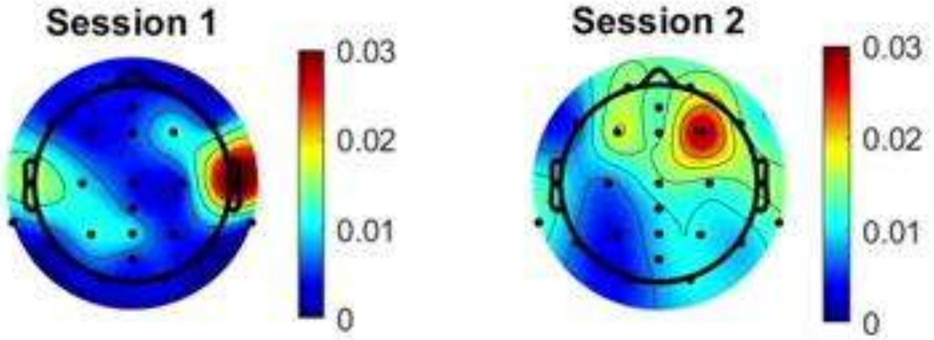
Feature weight consistency between sessions: audio & tactile

Subject 8

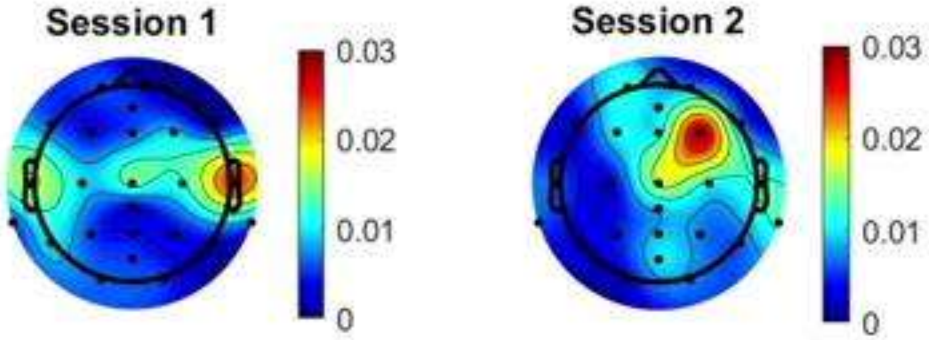
Audio – alpha band



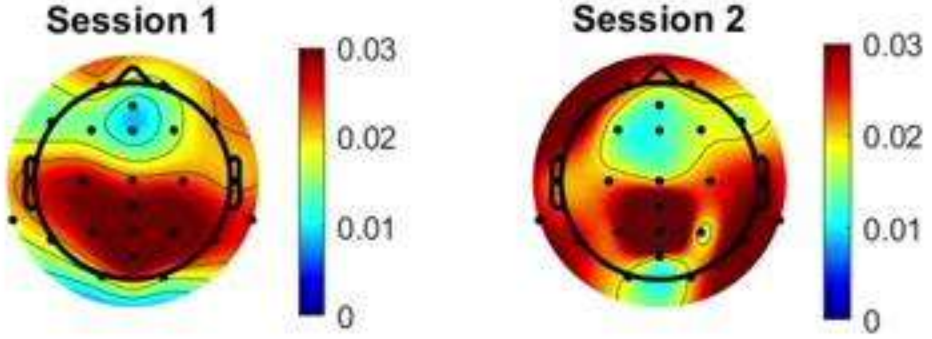
Audio – 37Hz



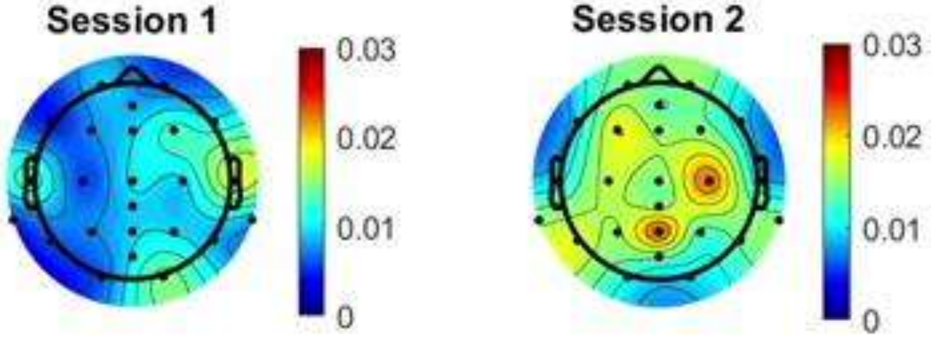
Audio – 44Hz



Tactile – alpha band



Tactile – 17Hz



Tactile – 27Hz