

Subject-independent Classification of Japanese Spoken Sentences by Multiple Frequency Bands Phase Pattern of EEG Response during Speech Perception

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Research motivation

■ Developing a brain computer interface (BCI) for communication

- ❑ Communication prosthesis for locked-in syndrome patients
- ❑ For real-time speech communication without body movement

BCI for online speech communication

- **Electrocorticography (ECoG)-based real-time vowel synthesizer** (Guenther et al., 2009)

- based on invasive method
- Higher accuracy

Our goal

- **EEG (Electroencephalography)-based BCI to convey speech in real time**

- EEG-based:
 - Relatively low cost + Compact
 - Non-invasive method
- But, difficult task

Our focus in the current study

■ Non-invasive neural decoding of speech (EEG/ MEG)

□ Imagined speech recognition

- 2 English words (Salama et al., 2014)
- 2 English syllables (D'Zmura et al., 2009)
- 2 Japanese vowels (DaSalla et al., 2009)

Our current purpose

improvement of spoken
sentence classification for BCI

□ Heard speech recognition

- 3 English sentences (Luo & Poeppel, 2007, etc)
- 5 English words (Chan et al., 2011), 2 English words (Correia et al., 2015)
- 32 English syllables (Wang et al., 2012)
- 8 English consonants (Wang et al., 2012)

Improvement points

Previous research (Luo & Poeppel, 2007, etc)

■ Language

- 3 **English** spoken sentences

■ Apparatus

- **Magnetoencephalography (MEG)**
 - Higher spatial resolution
 - Large + relatively high cost

■ Model training

- Construct **models for each participant**
 - New users have to collect their data
 - Time-consuming to collect a large amount of brain data from one person

■ Feature + classifier

- classifier: **template matching**
- features: **theta phase patterns**

Current research

- 3 **Japanese** spoken sentences

- **EEG**

- Poor spatial resolution
- Compact + low cost

- **Subject-independent model**

- Data collection is unnecessary before use
- Large data set by combining all user's data

- classifier: **support vector machine**

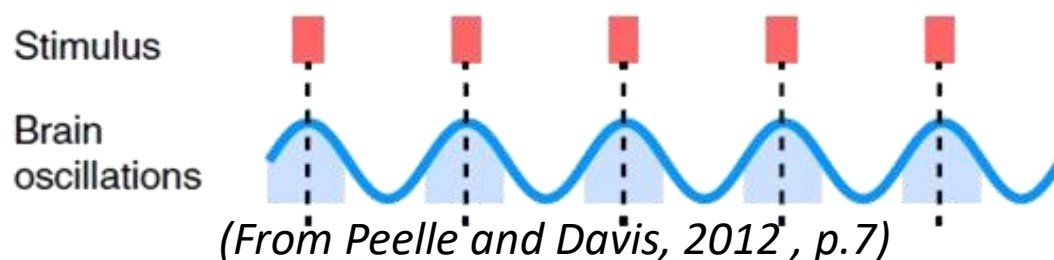
- suitable for fewer + high dim. dataset
- features: phase patterns in **various frequency bands**

Phase-locked responses

■ Neural oscillation tracks speech rhythm

□ Phase-locked responses

- Phase-matching between external rhythm & brain oscillation
- Extract linguistic information from speech



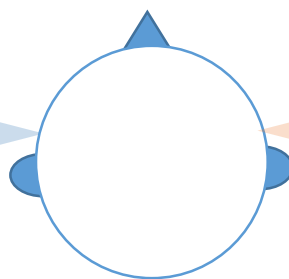
Left hemisphere

phonetic rhythm: ~ 25ms



phase-matching

low- γ oscillation: ~40Hz
(~ 25ms)



Right hemisphere

syllabic rhythm: ~ 125-250ms



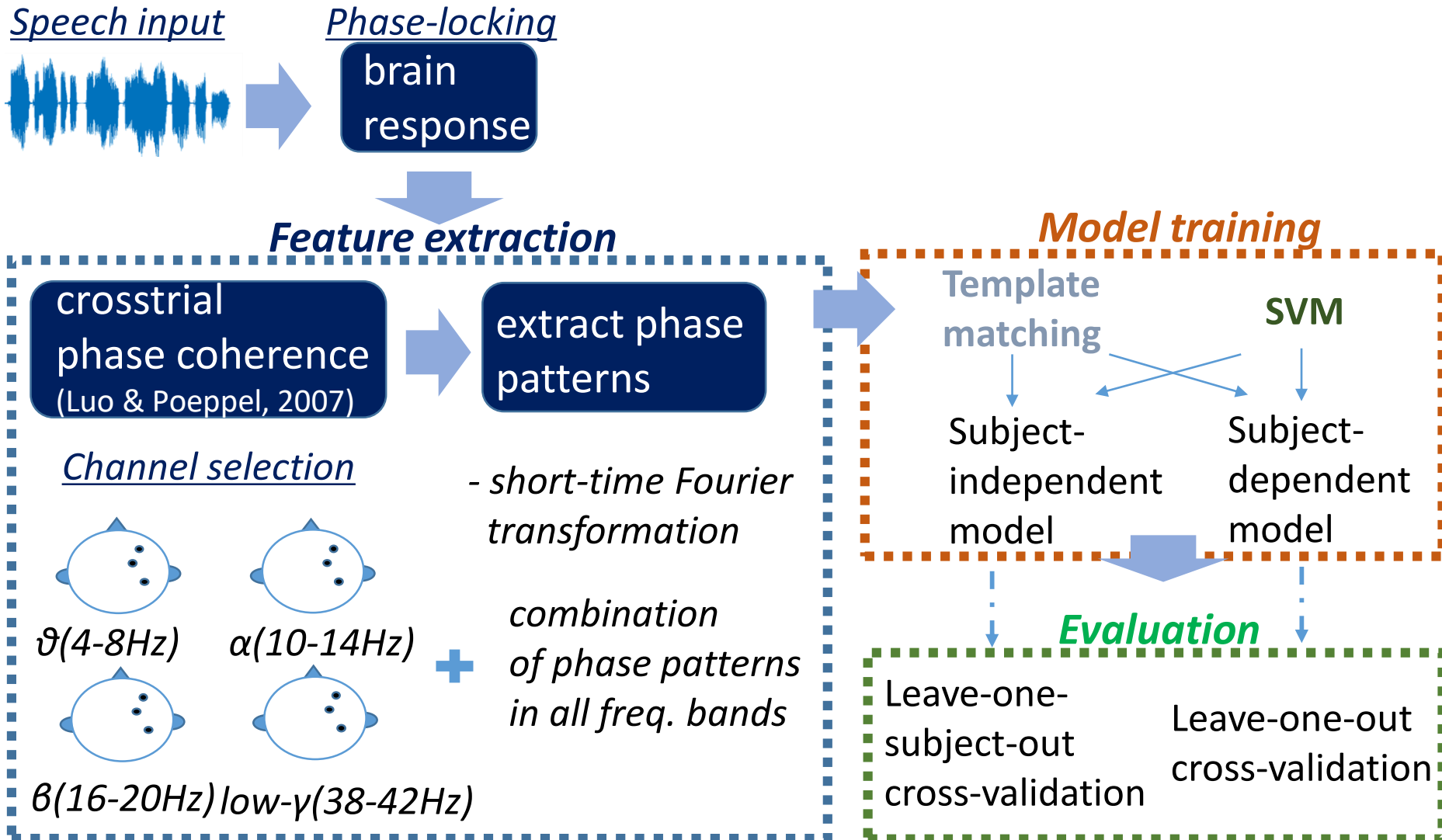
phase-matching

θ oscillation: ~4-8Hz
(~ 125-250ms)

(Poeppel, 2003; Luo & Poeppel, 2012)

- phase patterns inducing by phase-locked responses:
 - less individual differences (Kerlin et al., 2010)

Flowchart of classification



EEG data collection

■ EEG data collection

□ Participants

- L1 10 Japanese speakers (age: $\mu=24.3$; 1 participant was excluded)

□ Speech stimuli

- 3 Japanese spoken sentences
- Average duration: 3,146 ms

□ Stimuli presentation

- 24 times/ speech = total 72 presentation
- Total # of trials = 605 trials (after artifact rejection + preprocessing)

Results

Phase-locked responses

■ Crosstrial phase coherence

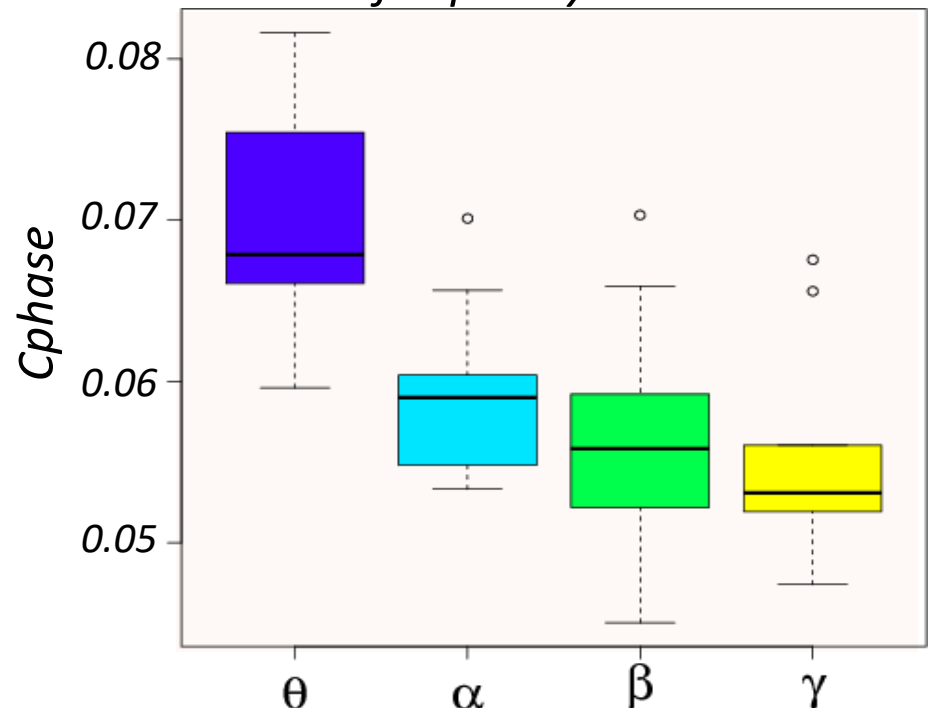
(Cphase; Luo & Poeppel, 2007)

- Calculated **per channel**
- how consistent phase values are in **each frequency band among trials**

$$\theta > \alpha, \beta, \text{low-}\gamma$$

($p < .05$, paired t-tests with Holm's p-value adjustment)

Boxplot in all subjects' Cphase in each frequency band



Cphase distribution map

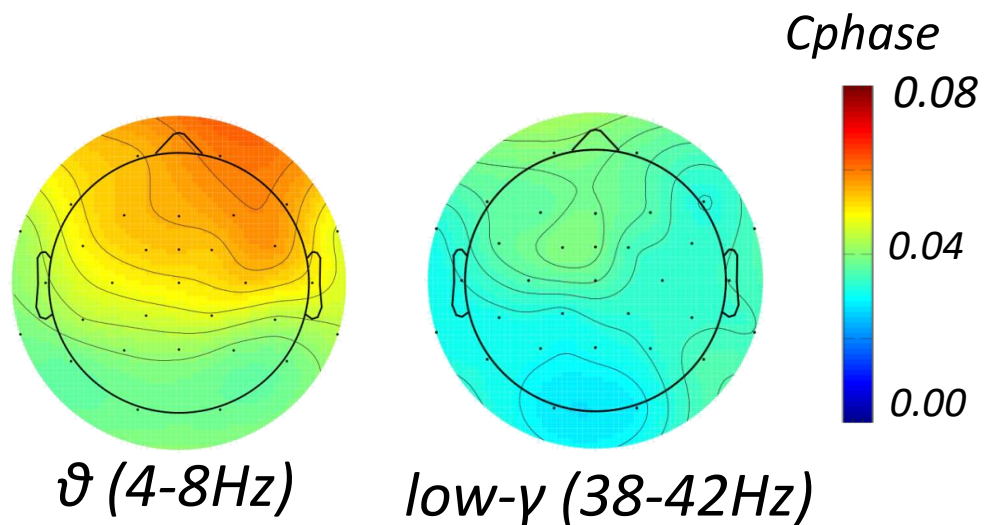
■ Cphase distribution map

□ theta

- Right hemisphere lateralization

□ low-gamma

- Tendency of left lateralization



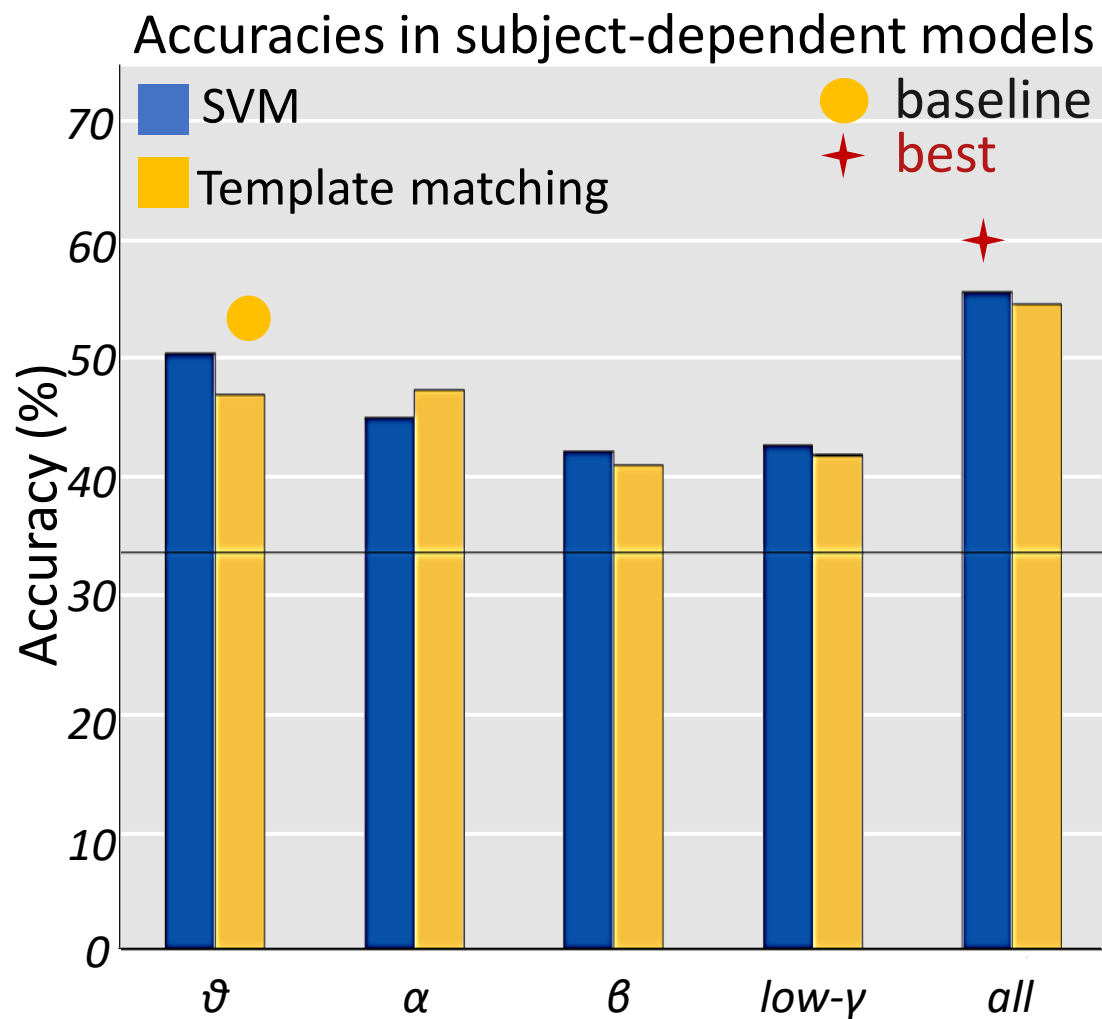
Subject-dependent models

□ Accuracy improvement

- Template matching by θ : 46.6%
- SVM by 'all': 55.2%
- + 8.6% ($p < .05$)

□ Differences b/w classifiers

- No differences in 'All' feature



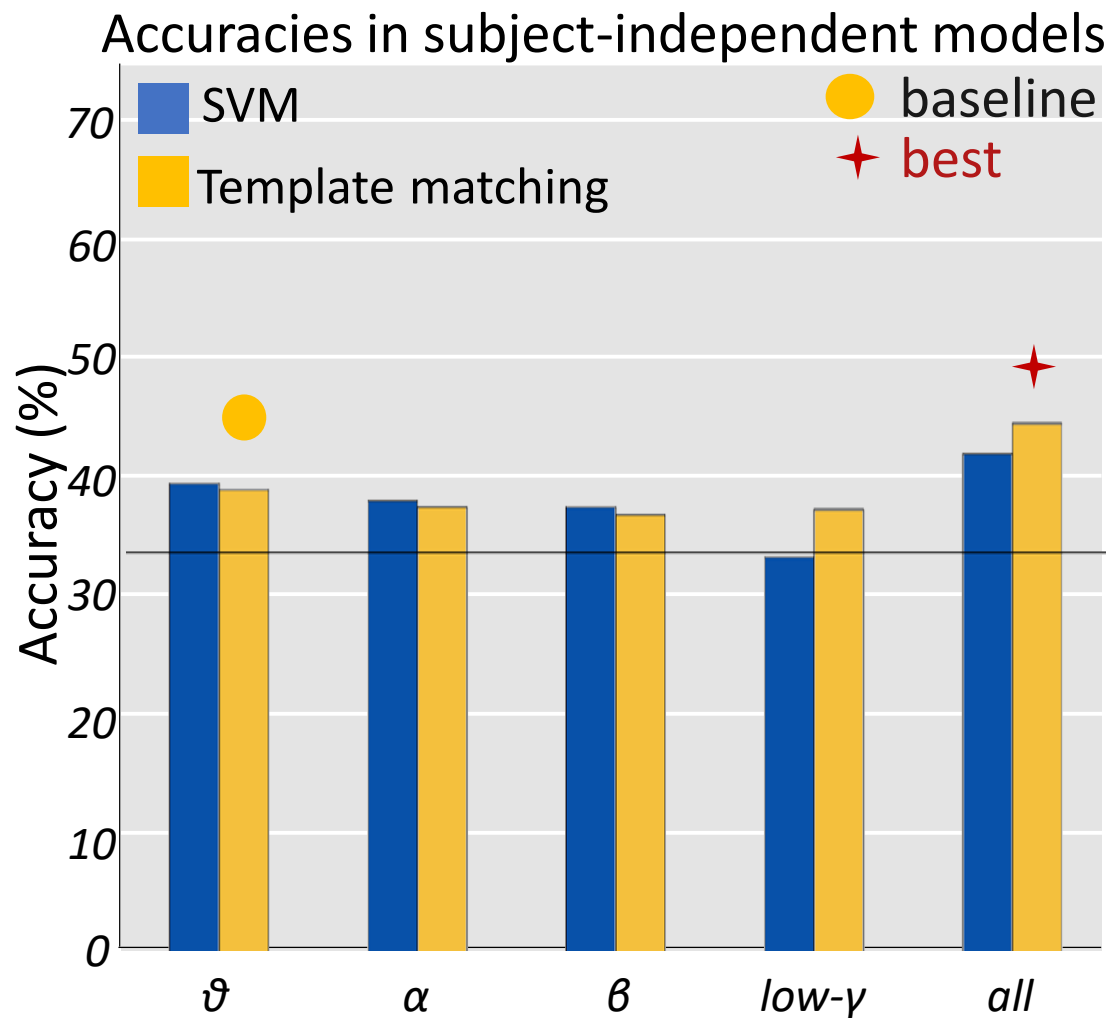
Subject-independent models

□ Accuracy improvement

- Template by θ : 38.5% ($p < .05$)
- Template by 'all': 44.0% ($p < .05$)
- + 5.5% ($p < .054$)

□ Differences b/w classifiers

- No differences in 'All' feature



Discussion + Future plan

■ Phase-locked responses to Japanese spoken sentences

- syllable tracking in theta
 - tracking acoustic feature (Howard & Poeppel, 2010)
 - syllable timing: consistent across languages
- phoneme tracking in low-gamma: Not conclusive
 - might be partially due to low S/N ratio in higher frequency band

■ Classification performances

- Accuracy improvement in 'All' feature
 - above chance-level in subject-independent classification
 - based on neurophysiological speech perception model (Poeppel, 2003, etc)
- SVM: no better performances than template matching

■ Future plan

- Other classification algorithm + more amount of data
- application to imagined speech recognition

References

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Thank you for listening

How to calculate Cphase

