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# Neural Language Decoding based on Speech Imagery Paradigm for Intuitive Brain-Computer Interface

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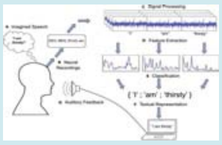
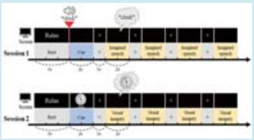
## Introduction

◆ Goals
- Recognize intuitive speech imagery based on Electroencephalogram(EEG) signals for generating neural commands
- Classification four speech imageries (open, grasp, flexion, extension) to applying robot control

◆ Related Works



Cooney et al., 2018



Lee et al., 2019

## Experimental Protocols

◆ Experimental Setup
- Subjects (3 males and 2 females, 27±3 years)
- EEG signals recording
  - 64 channels, 60 Hz notch filter, 100 Hz sample rate

Fig. 1. Experiment Environment

◆ Experimental Paradigm
- Rest (3s), Visual cue (2s), Fixation cue(1s), and Speech imagery Tasks(2s)
- Performing speech imagery task only during session
- Types of speech imagery tasks
  1) Hand grasping
  2) Hand open
  3) Arm flexion
  4) Arm extension

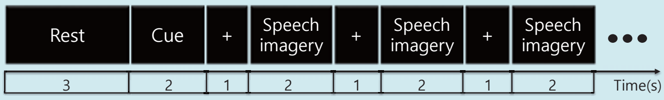



Fig. 2. Experimental Paradigm

## Data Analysis

◆ Data Preprocessing
- All The EEG data were band-pass filtered to the frequency range of 8-30 Hz
- Recorded 64 EEG channels according to 10/20 international system

◆ Feature Extraction and Classification
- Apply to common spatial pattern (CSP) filter
- Select the classification models based on ML*
  1) Linear discriminant analysis (LDA)
  2) Linear support vector machine (SVM)
     - Kernel function: Linear
  3) Subspace ensemble classifier (SEC)
     - Subspace dimension: 30
  4) Deep neural network (DNN)
     - Number of fully connected layers: 1
     - First layer size: 100
     - Activation function: ReLU
     - Iteration limit: 1000
- Validation: 5-fold cross validation

* Machine learning

*Table 1. Comparison of Classification Accuracy*

| Subjects | LDA | Linear SVM | SEC | DNN |
|---|---|---|---|---|
| Sub 1 | 40.0% | 35.5% | 39.8% | 37.5% |
| Sub 2 | 31.5% | 31.6% | 31.1% | 31.8% |
| Sub 3 | 31.8% | 32.9% | 36.0% | 32.4% |
| Sub 4 | 32.1% | 30.6% | 31.2% | 29.1% |
| Sub 5 | 30.9% | 27.5% | 32.9% | 30.0% |
| **Average** | **33.26%** | **31.62%** | **34.2%** | **32.16%** |

## Experimental Results

◆ The subspace ensemble classifier achieved the highest performance on average

◆ The classification results of Sub 1 showed the highest performance across all subjects

◆ Fig. 3 is the Sub 1's confusion matrix by LDA with 40.0%
- True positive rate of the classification is higher than the chance level accuracy (approximately 25%)

◆ Fig. 4 is the scalp plot of Sub 1
- Speech imagery for command mainly activates the posterior of brain

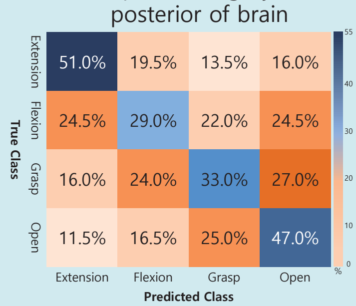



Fig. 3. Confusion Matrix

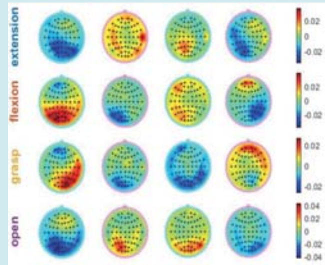



Fig. 4. Scalp Plot

## Discussion and Conclusion

◆ The classification results of some subjects showed still low to apply real-time neural decoding from EEG

◆ Need to improve the classification performance
- Modifying the parameter SVM and DNN model
- Adapting the GRU model for considering time series data
- Applying the advanced EEG data augmentation method (e.g. SMOTE, Sliding window method)

## References

1) Ciaran Cooney et al., "Neurolinguistics Research Advancing Development of a Direct-Speech Brain-Computer Interface" *iScience*, Volume 8, 2018, pp.103-125.
2) S.-H. Lee, M. Lee, J.-H. Jeong and S.-W. Lee, "Towards an EEG-based Intuitive BCI Communication System Using Imagined Speech and Visual Imagery," *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, 2019, pp. 4409-4414.

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