Erasmus 2018

Electroencephalographic Study for Human Speech Processing

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Outlines

- Part I. Neuromorphic Speech Classification via EEG Signals
- Part II. Multiclass EEG Discrimination with Speech Imagination (Vowels and Words)
- Part III. Future Study Direction
- Part IV. My Lab (BMSSA) & Other Researches

Part I.

Neuromorphic Speech Classification Based on EEG Signals

J. Neural Eng. 11 (2014) & Scientific Reports 5 (2015)

Background

- Neurolinguistics - Neural mechanisms of language processing
- Perception of speech sounds is categorical.

- Previous studies on the neural correlates of categorical perception have used mismatch negativity (MMN).
  - Event-related potential (ERP) that occurs in response to an infrequent change in a repetitive sequence of stimuli
  - Brain's capability to perform automatic comparisons between successive stimuli

- Most studies try to elicit the MMN to identify the brain's capability for phoneme change detections, by averaging over multiple trials and subjects.

Background

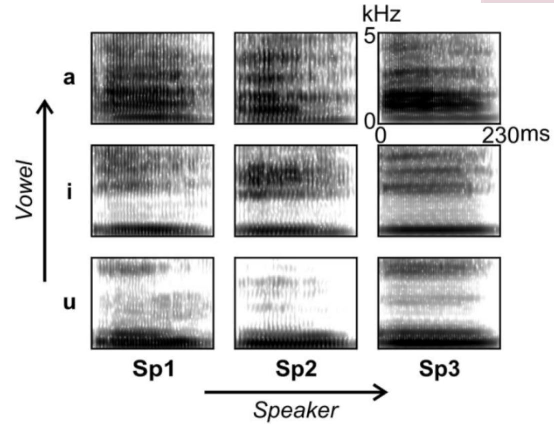
- In this study, we intend to discriminate the brain responses to three Korean vowels **/a/, /i/ and /u/** for each trial,
  - Auditory steady-state response (ASSR) - based paradigm
  - Pattern recognition
  - Signal processing techniques.

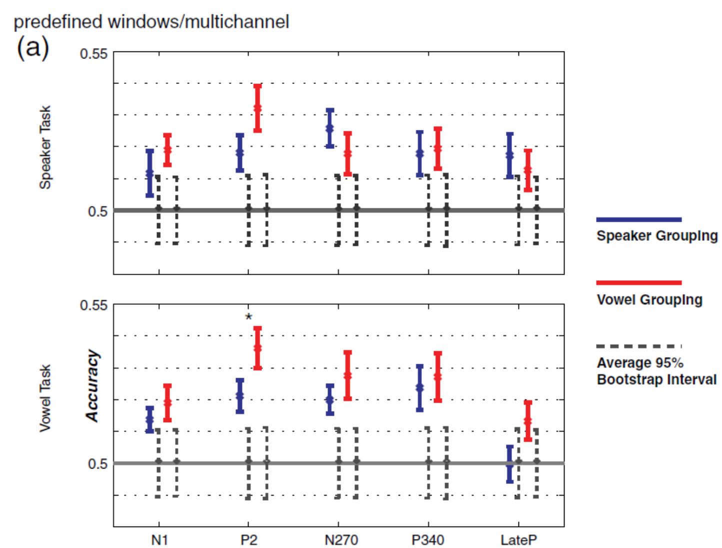
Objectives

- To find components related to phoneme representation
- To discriminate EEG responses on a single trial basis

Background

- Dutch vowel sound are presented: /a/, /i/, and /u/
  - by 3 native Dutch speakers (2 female, 1 male)
  - During one-back task
- Speaker grouping and Vowel grouping for the analysis
  - Speaker Grouping: sp1 vs. sp2, sp1 vs. sp3, sp2 vs. sp3
  - Vowel Grouping: /a/ vs. /i/, /a/ vs. /u/, /i/ vs. /u/
- Accuracies were obtained by averaging results of the respective 3 binary comparisons.
- P2 Interval : Largest average accuracies
  - During both the speaker and vowel grouping.





Hausfeld et al. Neuroimage. 2012.

Vowel Stimuli Selection

- Phonemes with different formant frequencies (F2) evoke different levels of MMN. Naatanen R *et al* 1997
- Tongue body positions for /u/, /i/, and /a/ are high-back, high-front, and low-back, respectively.
- Large difference in their formant frequencies Stevens 2000

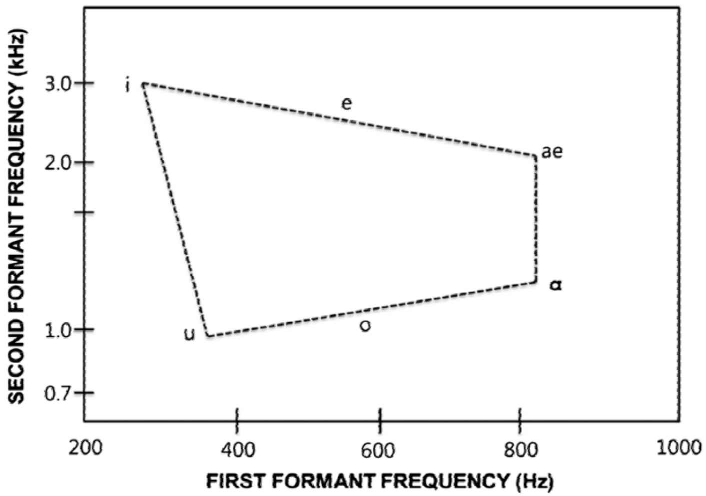


Figure 1. Formant frequencies of vowels. Data points for /i/, /u/, /a/ and /æ/ are averages from Peterson and Bamey (1952).

/a/, **/i/**, **/u/** were selected for evoking distinct brain responses

Vowel Stimuli Selection

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- Tongue body positions for /u/, /i/, and /a/ are high-back, high-front, and low-back, respectively.
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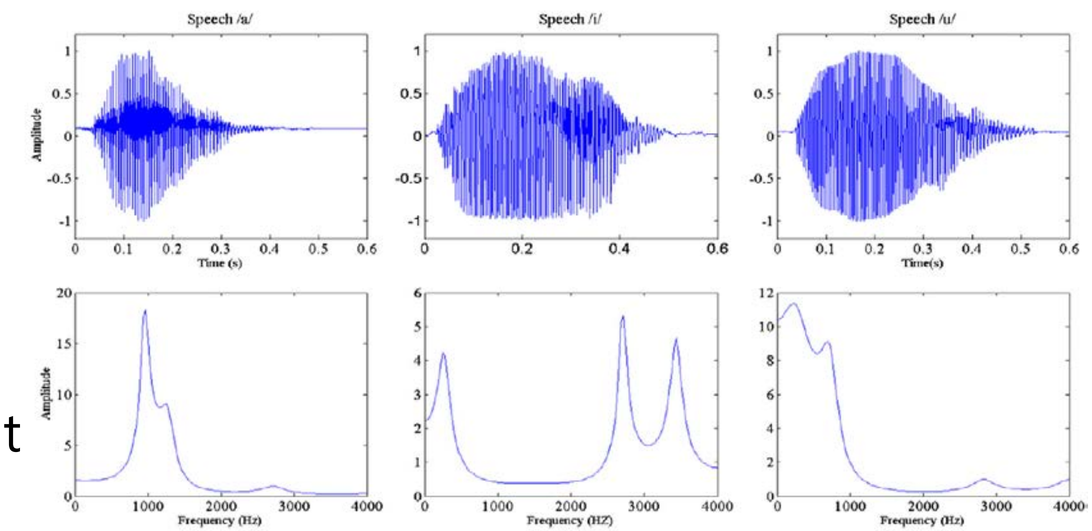


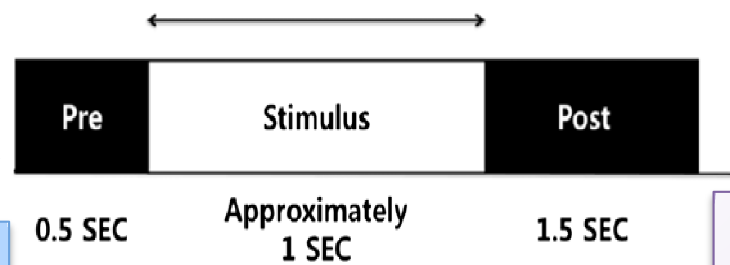
Figure 2. The time course (first row) and the linear predictive coefficient (LPC) spectra (second row) of three Korean vowels used in our experiment. The peaks of LPC spectra refer to the formant frequencies of speech signals. Vowel /a/ shows peaks at F1 = 951 Hz, F2 = 1285 Hz, and F3 = 2722 Hz; vowel /i/ at F1 = 270 Hz, F2 = 2703 Hz, and F3 = 3430 Hz; and vowel /u/ at F1 = 258 Hz, F2 = 740 Hz, and F3 = 2819 Hz. All stimulus amplitudes were normalized to the range [−1, 1].

/a/, **/i/**, **/u/** were selected for evoking distinct brain responses

Data Acquisition and Experiment

- 64-channel EEG device (Electrical Geodesics, Inc.)
- International 10-20 system
- Sampling rate : 256Hz

Stimuli were randomly presented



A pre-stimulus interval of 0.5s
for baseline correction

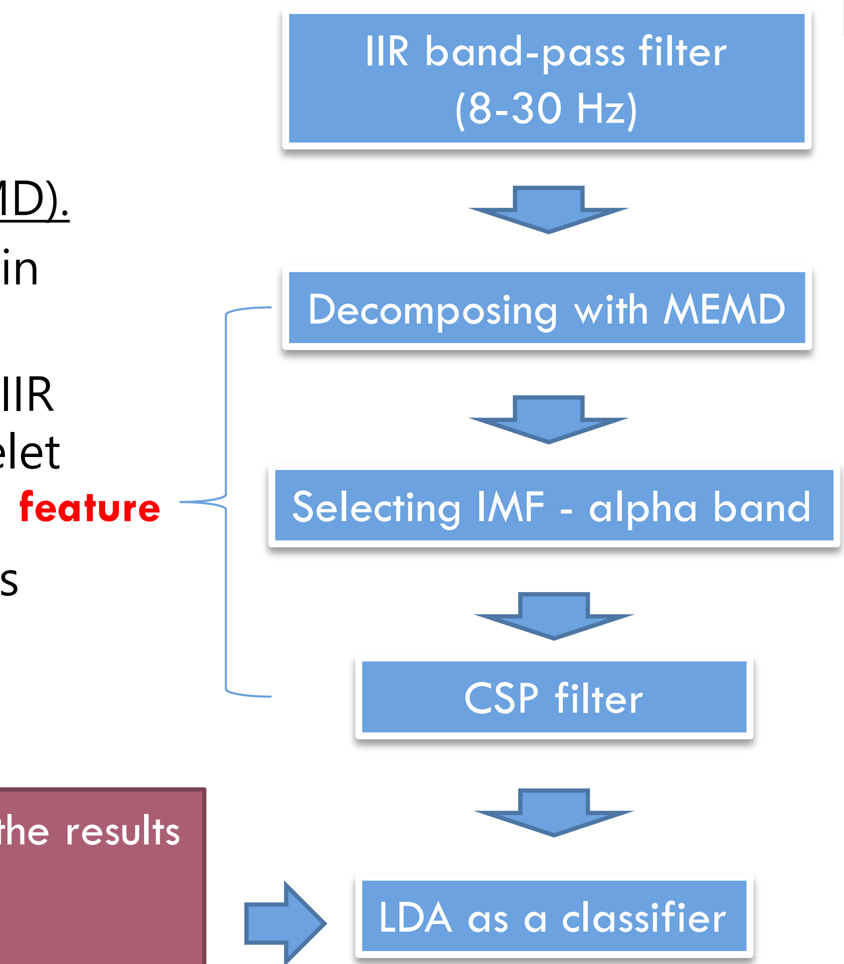
/a/, /i/, /u/

A post-stimulus interval of 1.5s
for preventing an overlap of brain responses

90 trials in a single session, 2 sessions
Total 180 trials per subject.

Overall Procedure for EEG Classification

- IIR band-pass filter (8-30 Hz)
- Decomposing EEG data into intrinsic mode functions(IMFs) by Multivariate Empirical Mode Decomposition (MEMD).
- Selecting IMFs which were dominant in the alpha band.
- Comparing the results of the MEMD, IIR band-pass filter, and continuous wavelet transform (CWT).
- Using CSP filter after those algorithms for enhancing the classification performance.
- Using LDA as a classifier.



Comparing the results
- MEMD
- CWT
- IIR

Frequency Band Selection Using MEMD

- Empirical mode decomposition (EMD) – fully data-driven method for time-frequency analysis of non-stationary and nonlinear signals.
- Main idea – iterative sifting procedure which decomposes a signal in a sum of IMFs.
- Criteria for an IMF

1. The numbers of extrema and zero-crossings are the same or differ at most by one.
2. The mean of the envelopes defined by maxima and the envelopes defined by minima is 0 over the entire region. It means that the envelopes have to be symmetric with respect to zero.

Frequency Band Selection Using MEMD

- EMD is only useful for analyzing univariate time-series signals, not for multivariate time-series signals.
- MEMD should be adopted for analyzing multivariate signals such as high-density multichannel EEG.

- Critical procedure of MEMD is calculating the local mean.
  - by averaging multiple multi-dimensional envelopes by projecting the multivariate signal along different directions
  - difficult to select suitable direction vectors.

Common Spatial Pattern Filter (CSP)

- Widely used for extracting the features from EEG data for BCI
- The purpose is to find the spatial filters
  - maximize the variance of signals in a class
  - minimize the variance in the other class at the same time
    - for the discrimination of two populations.

- Let the single-trial EEG data be represented as an $N \times L$ matrix E, where N is the number of channels and L is the number of sample points.
- First, EEG signals should be mean subtracted.
- The normalized spatial covariance of E can be acquired from

$$\boldsymbol{C} = \frac{\boldsymbol{E}\boldsymbol{E}^T}{trace(\boldsymbol{E}\boldsymbol{E}^T)}$$

  where T means the transpose operator and trace is the sum of the diagonal elements of the matrix.
- The spatial covariance $\overline{\boldsymbol{C}}_{f\in[/a/,/i/]}$ is obtained by averaging over the normalized spatial covariance matrices of all trials for each task group, /a/ or /i/.

Linear Discriminant Analysis (LDA)

- Optimal linear combination of features which differentiates the classes.
- Assumption: the distribution of observations or feature vectors is Gaussian with equal covariance matrix (Σ) for both classes.
- The likelihood of the observation $\mathbf{x}$ with a class y_i in m dimensions can be computed as

$$p(\boldsymbol{x}|y_i) = N(\boldsymbol{u}_i, \Sigma) = \frac{1}{(2\pi)^{m/2}|\Sigma|^{1/2}} exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{u}_i)^T \Sigma^{-1} (\boldsymbol{x}-\boldsymbol{u}_i)\right)$$

  - $\boldsymbol{u}_i$ and Σ are mean vector and covariance matrix of observation with class y_i, respectively.
- In case of two class classification, discriminant function can be computed as

$$\mathrm{g}_{ij} = \mathrm{g}_i(x) - \mathrm{g}_j(x) = \ln\big(p(\mathbf{x}|y_i)\big) P(y_i) - \ln\left(p\left(\mathbf{x}\middle|y_j\right)\right) P\left(y_j\right) = \mathbf{w}^T\mathbf{x} + \mathbf{b}$$

  - Projection vector $\mathbf{w}$ and bias term $\mathbf{b}$ are computed using training set.

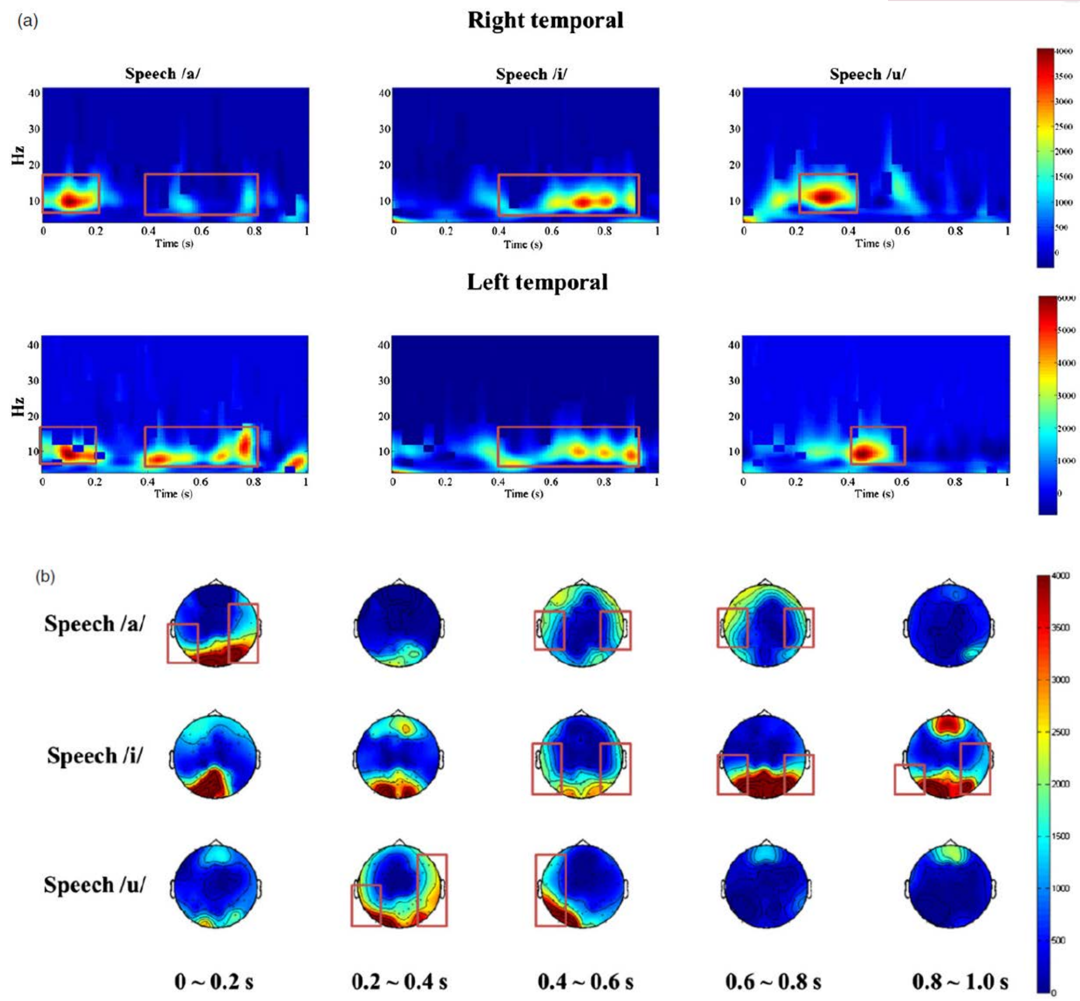
$$\mathbf{w}^T = \left(\Sigma^{-1}(\boldsymbol{u}_i - \boldsymbol{u}_j)\right)^T$$

- The LDA classifier assigns an observation vector of test to the class label according to sign($\mathbf{w}^T\mathbf{x} + \mathbf{b}$)

Time-Freq. Analysis - Grand Average

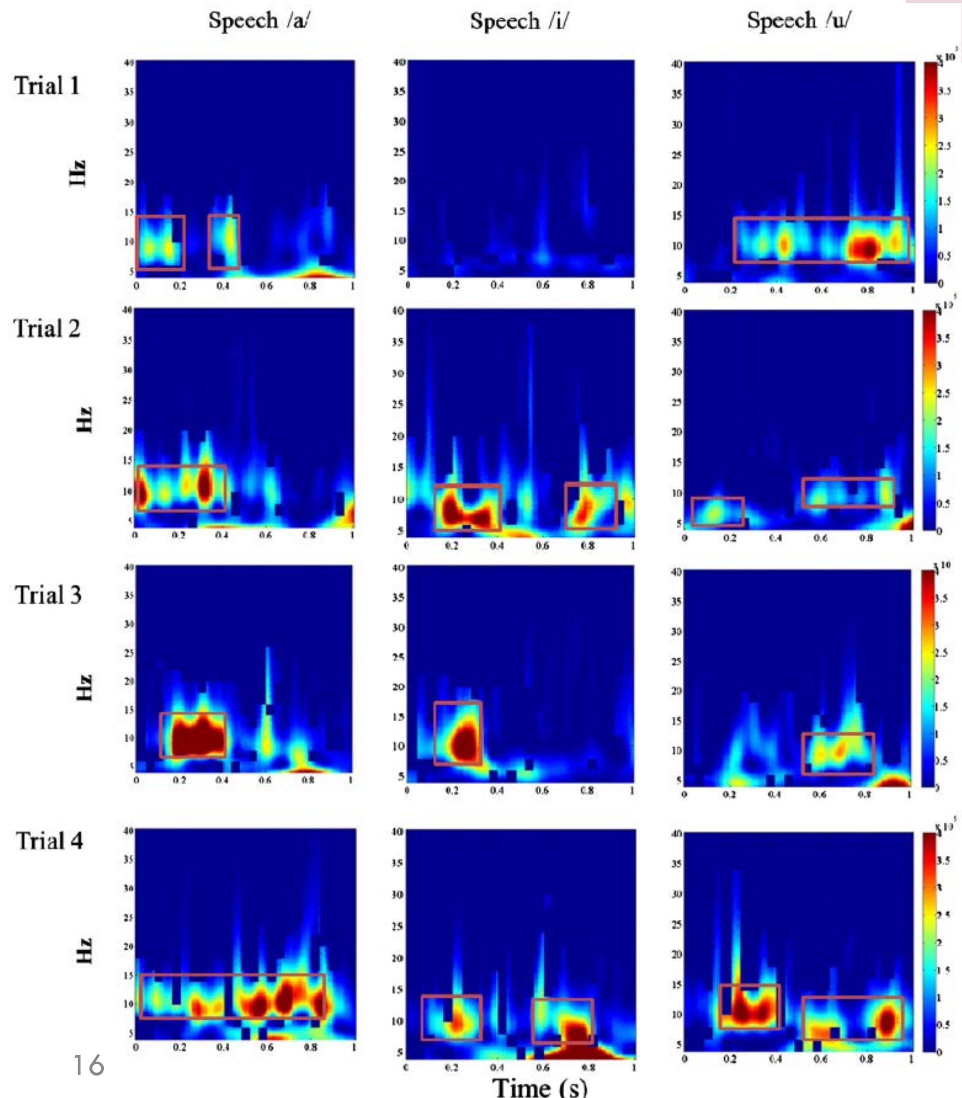
- Statistically different alpha band power in both right and left temporal areas between the three experimental conditions

- Distinct responses for the three vowels in the temporal region of topography



Time-Freq. Analysis – Single Trials

- Much of the alpha band power in almost all trials is statistically different between the three experimental conditions.
- We assumed that alpha band components are related to our stimuli



Classification of Real EEG Recordings

- 10-fold cross validation was applied
- MEMD showed better overall classification accuracies than CWT and IIR band-pass filter. (one-tailed *t*-test p<0.01)

Subject	Feature	/a/vs/i/	/a/vs/u/	/i/vs/u/	Overall
S1	BPF	62.50 ± 10.51	63.82 ± 14.63	55.97 ± 16.42	60.76 ± 12.25
	CWT	65.77 ± 9.97	61.45 ± 17.23	58.18 ± 11.02	61.80 ± 11.61
	IMF2	**71.41 ± 10.62**	**67.46 ± 9.78**	**67.89 ± 8.09**	**68.92 ± 8.59**
S2	BPF	60.36 ± 10.24	60.00 ± 8.23	62.95 ± 17.81	61.10 ± 11.09
	CWT	59.25 ± 15.12	61.52 ± 7.11	63.11 ± 16.60	61.29 ± 12.44
	IMF2	**72.16 ± 11.85**	**69.02 ± 10.61**	**69.41 ± 7.59**	**70.19 ± 9.89**
S3	BPF	73.82 ± 15.86	52.31 ± 12.47	52.20 ± 13.13	59.44 ± 12.62
	CWT	67.91 ± 13.91	56.35 ± 8.33	56.02 ± 14.56	60.09 ± 11.76
	IMF2	**74.00 ± 12.29**	**65.90 ± 9.10**	**70.12 ± 13.75**	**70.00 ± 11.17**
S4	BPF	68.91 ± 10.83	63.45 ± 12.16	58.43 ± 12.90	63.59 ± 11.26
	CWT	68.13 ± 15.63	64.38 ± 11.11	56.00 ± 10.61	62.83 ± 11.65
	IMF2	**75.85 ± 14.38**	**71.29 ± 10.11**	**67.50 ± 10.49**	**71.54 ± 10.76**
S5	BPF	60.00 ± 14.14	44.91 ± 12.05	68.18 ± 10.08	57.69 ± 11.69
	CWT	61.00 ± 15.95	55.91 ± 23.07	63.73 ± 13.37	60.21 ± 16.56
	IMF2 + 3	**71.00 ± 14.49**	**65.45 ± 12.76**	**71.27 ± 16.62**	**69.24 ± 13.72**
S6	BPF	62.79 ± 17.16	55.39 ± 14.97	60.73 ± 19.76	59.63 ± 16.62
	CWT	65.88 ± 17.64	63.46 ± 11.47	51.00 ± 16.79	60.11 ±14.5
	IMF2	**71.43 ± 13.29**	**69.68 ± 11.59**	**69.45 ± 15.79**	**70.18 ± 13.15**
S7	BPF	58.48 ± 13.78	**65.17 ± 13.96**	57.31 ± 10.34	60.32 ± 11.84
	CWT	49.09 ± 17.12	53.89 ± 11.82	61.28 ± 16.40	54.75 ± 15.03
	IMF2	**69.21 ± 15.78**	64.86 ± 13.12	**68.95 ± 15.46**	**67.67 ± 13.87**

Consideration

- Using ASSR-based paradigm which provided time-series information
- Most of the alpha band power of grand-averaged EEG was statistically different between the three experimental conditions
  - alpha bands might be speech-related responses

- MEMD-based classification extracted the speech-related more precisely than the conventional methods such as CWT, BPF.

- In future studies, we expect to apply our approach to a brain–computer interface (BCI) technology aimed at allowing patients who cannot move spontaneously to communicate by using their brain signals.

- Possibility of using vowel speech sounds instead of pure tone sounds in ASSR-based BCI system.
- For clinical fields such as diagnosis and rehabilitation for people with speech and language disorders.

Hardware Neural Network

Artificial Neural Network (ANN)

- Effective method of processing large datasets: pattern recognition, classification, and clustering
  - Software-realized artificial neural network (ANN)'s operating speed is insufficient for increasingly complex networks.
  - Hardware neural network (HNN) has a clear speed advantage.
- Currents limitation of HNN
  - Analogue circuits require too much power
  - Digital approaches use too many transistors in a single synaptic device
- To make advanced HNNs, synaptic devices must satisfy two condition

1. simple, two-terminal architecture - allowing high density to be achieved via a cross-point array
2. The weight of the devices should change gradually with the bias voltage, and the rate at which the weight increases and decreases should be symmetric.

Hardware Neural Network

Expectation

- Memristive synapses have simplicity and functional similarity to a synapse.
- Phase-change memory (PRAM), conductive-bridge memory (CBRAM), and oxide based memory (RRAM) have memristive characteristics

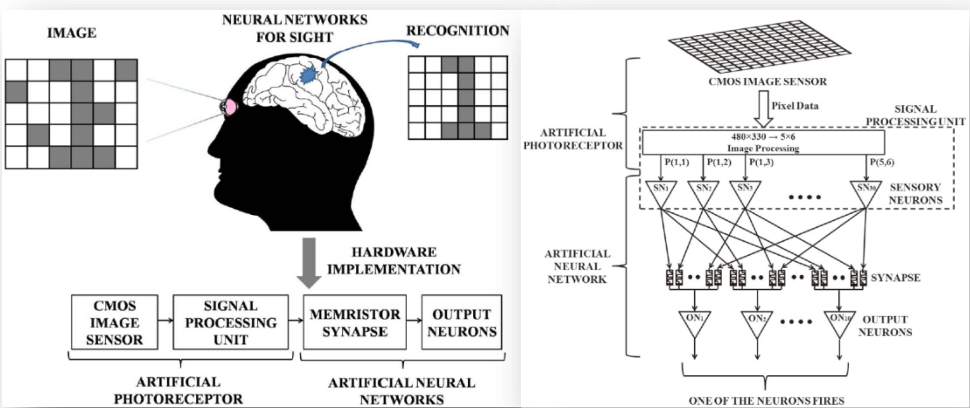
Limitation

- The conducting filament formation of current memristive synapse causes significant variations in resistance
  - Preventing the desired gradual and symmetric change in conductance

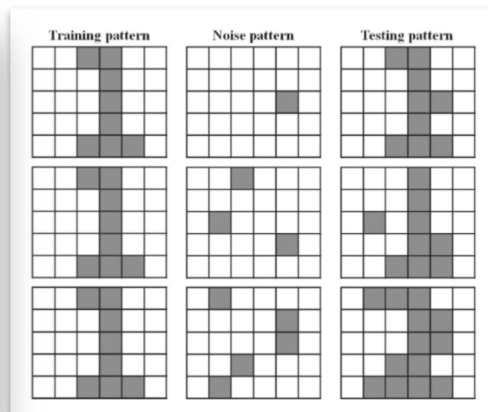
Hardware Neural Network

- Neuromorphic system for visual pattern recognition
  - PCMO-based memristor array and CMOS image sensor (CIS)
  - The system has been successfully demonstrated by training and recognizing number images from 0 to 9.

Proposed neuromorphic system



Recognition rates for various noisy patterns



Noise level (No. of noise pixel/30)	Recognition rate
0%	100%
3%	95%
10%	85%
16%	55%

Chu et al. IEEE Transactions on Industrial Electronics. 2015.

Hardware Neural Network

- In the present study,
  - High-density cross-point memristive synapse array with improved synaptic characteristics
  - Describe a learning scheme to mitigate the unintended switching problem often encountered with cross-point arrays

- The conductance of the proposed system changes <u>more gradually and symmetrically</u> in the presence of voltage pulses above a certain threshold voltage.
  - Otherwise the synapse retains its conductance

Implication of the study

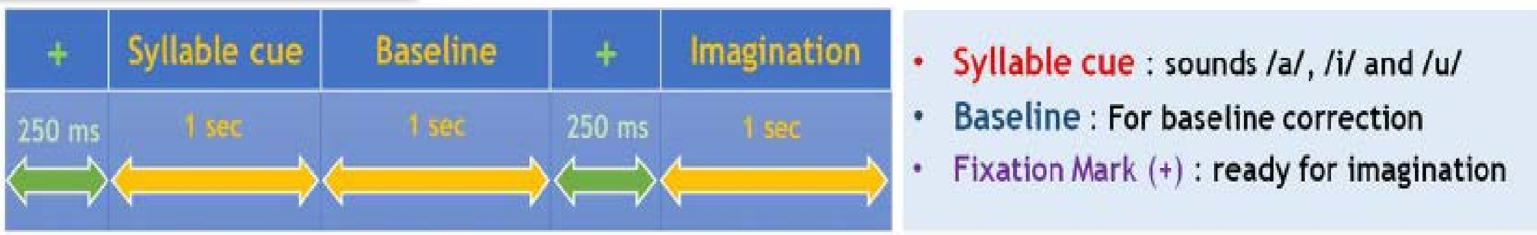
- The first primitive prototype of an electronic system that utilizes a cross-point memristive synapse array <u>for EEG pattern recognition</u>.

EEG Experiment: Speech Imagery

- Using 64-channel EEG device by Electrical Geodesics, Inc.
- Following international 10-20 system, electrodes were located.
- Sampling rate : 250Hz

Experimental paradigm

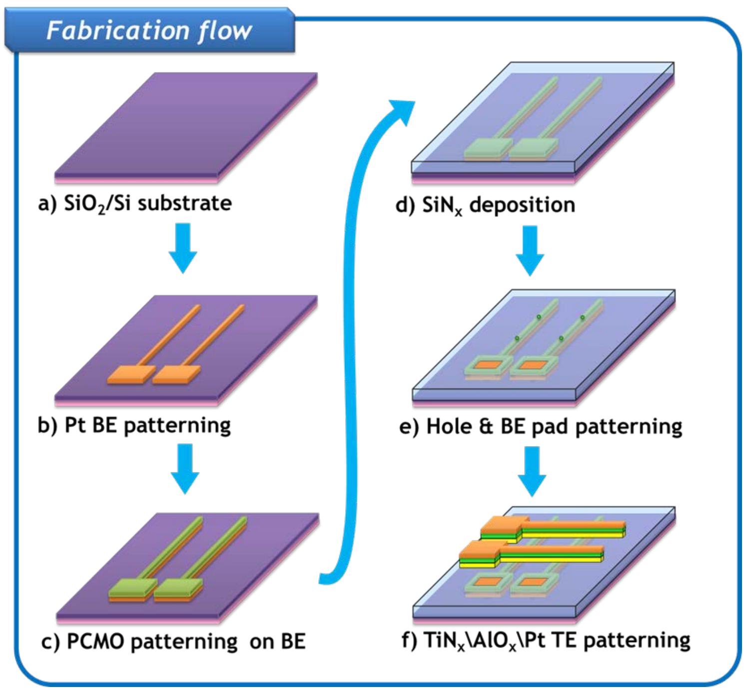
a



- Total length of each trial is 3.5s.
- 100 trials for each syllable.
- IIR band-pass filter (8-30 Hz) -> Baseline correction -> MEMD -> CSP -> Binarization

Structure and Fabrication of Memristive Synapses

- Cross-point memristive synapse array



Si wafer cleaning
SiO_2 oxide layer

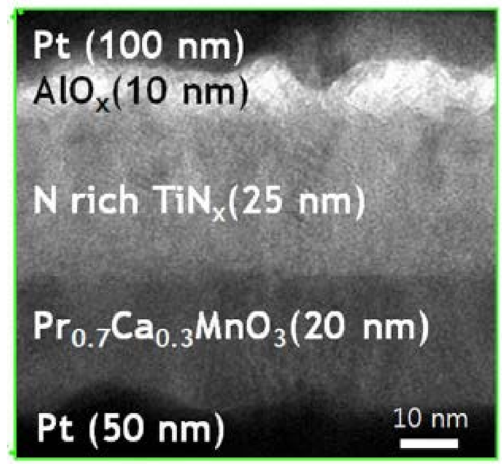
Pt bottom electrodes

Polycrystalline PCMO film

SiN_x layer

Hole and BE pad patterning

Top electrode patterning, consisted of TiN_x, AlOx and Pt



System Description

1st Block

- Mainly realized in software
  - Captures EEG signals
  - Extract the distinct features of 3 vowels
  - Convert into a series of 32-bit binary code for the 32 pre-neurons to generate a spike signal.

2nd Block

- Single-layer neural network
  - 32 pre-neurons
  - 192 memristive synapses
  - 6 post-neurons

- Pre-neurons are hard-coded into a FPGA
- Synaptic interconnection: 192 memristive synapses in a cross-point synapse array
- Post-neurons : a leaky integrate-and-fire neuron

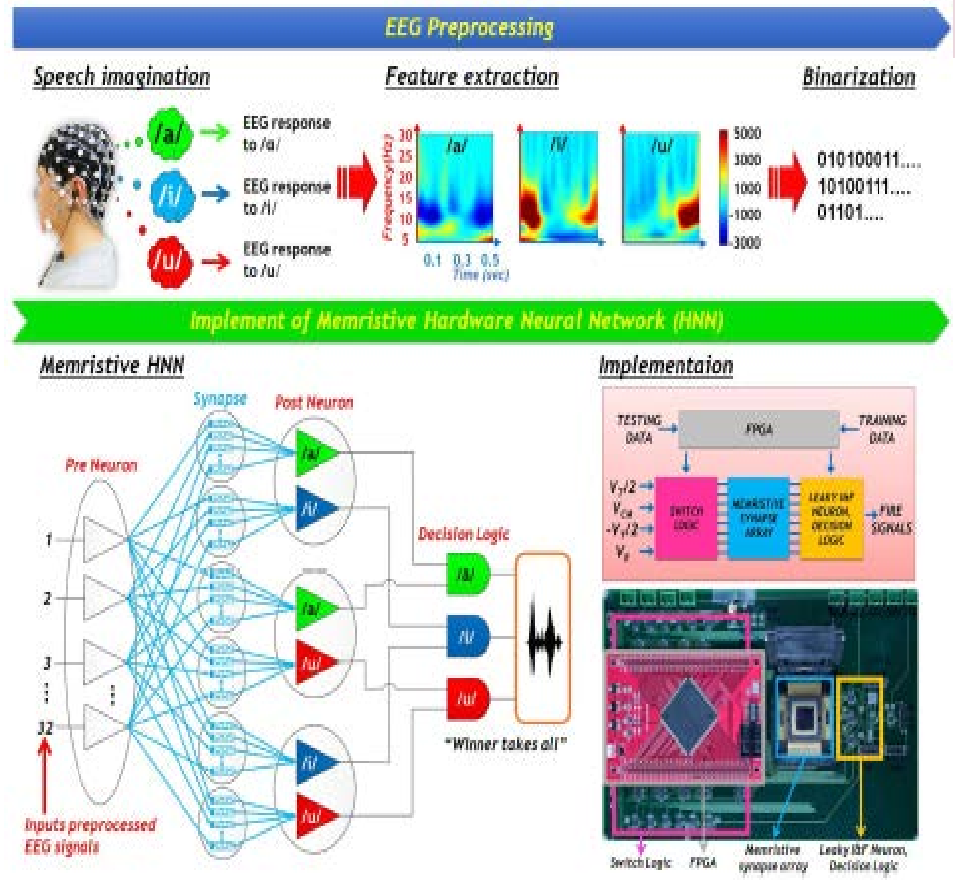
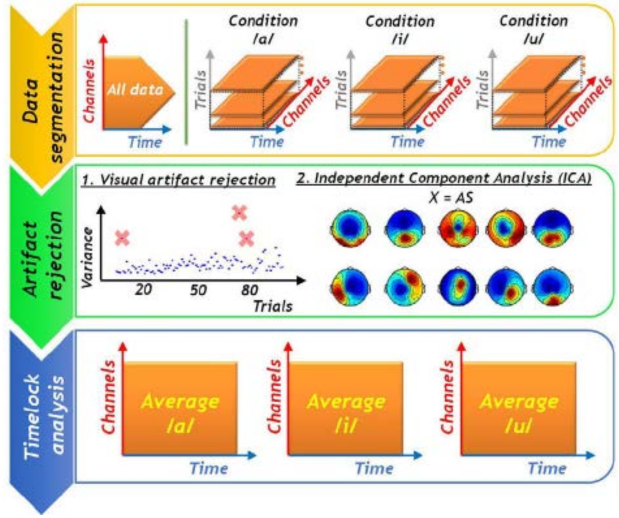
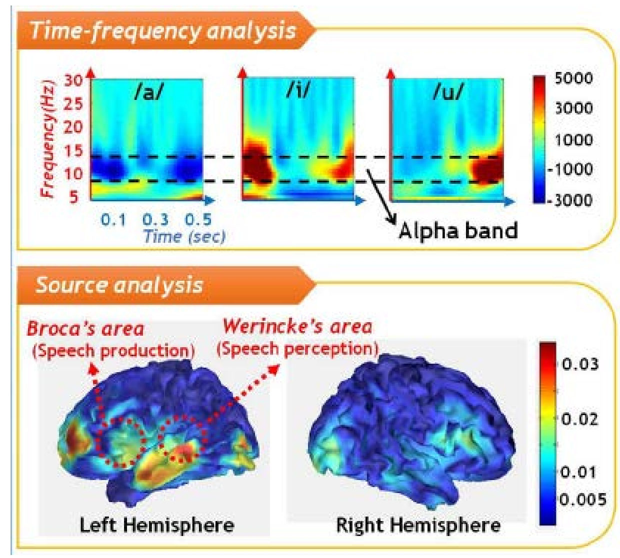


Figure 1. Proposed memristive HNN system for EEG pattern recognition. Schematic illustrations and images of components for a proposed electronic system with memristive synapse. It can be categorized by two approaches: EEG preprocessing and implement of memristive hardware neural network.

EEG Analysis of Imagined Speech

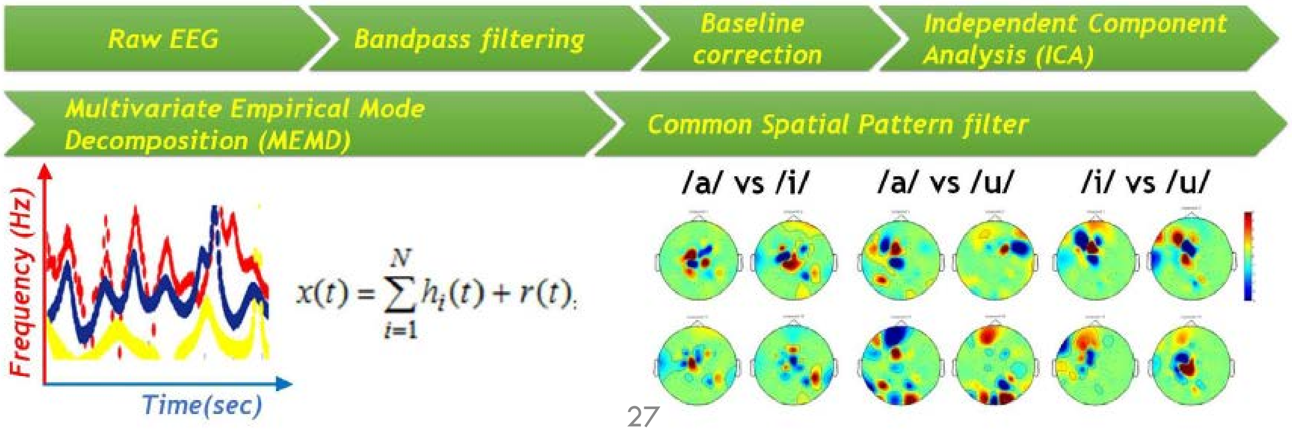
- Segmentation of data into each condition & trial
- Artifact rejection
- Time-lock analysis
  - Average the EEG data over all trials for each condition
- Time-Frequency analysis with Morlet wavelet
  - The alpha band (8-12 Hz) activities of each vowel are distinct
- Source localization using a Laplacian-weighted current density estimator
  - The current sources of the data were located close to Broca's and Wernicke's area





EEG Analysis of Imagined Speech

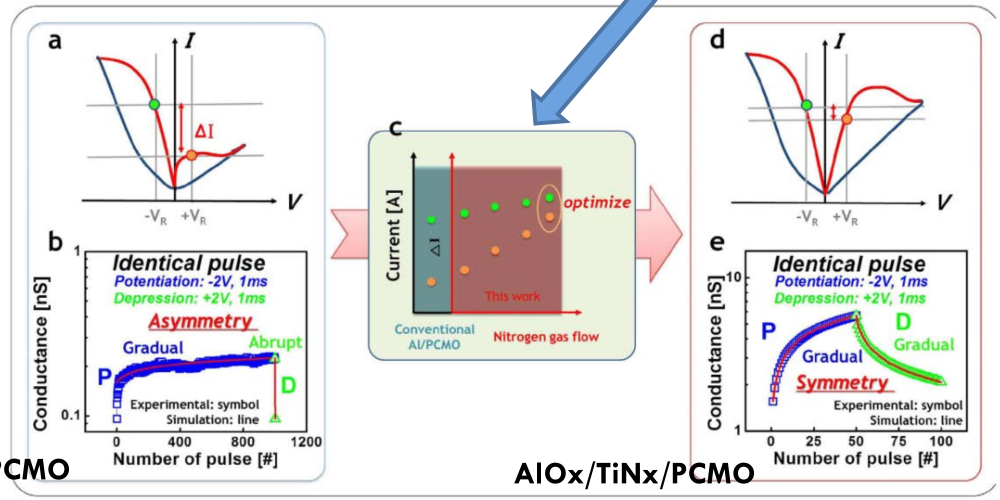
- Feature extraction for the classification by memristive system
  - IIR band-pass filter - Butterworth order: 5, bandwidth: 8–30 Hz
  - Baseline correction using pre-stimulus period to eliminate residual noise
  - Independent Component Analysis to eliminate artefacts
  - Multivariate Empirical Mode Decomposition
    - Decompose the EEG data into intrinsic mode functions (IMFs)
  - Common Spatial Pattern Filter
    - Enhance the classification performance
  - Binarize the extracted feature for input to the H/W



Considerations for Implementing a Cross-Point Memristive Synapse Array

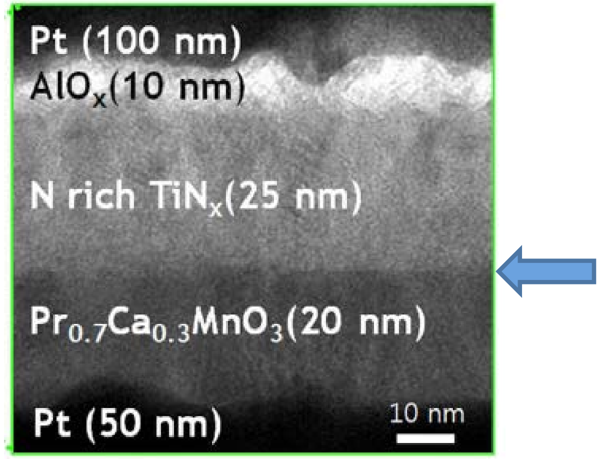
- For the simplicity of the architecture of HNN
  - Identical pulses
  - simple cross-array structure with two terminals.
- Responses of Advanced synaptic behavior in both potentiation and depression
  - Gradual
  - Symmetric

New process to minimize the inhomogeneous barrier



Al/PCMO

AlOx/TiNx/PCMO



Memristive HNN Learning

- The firing neuron is predetermined by the label data
  - synaptic weights are updated by feature codes, allowing the predetermined neuron to fire.
- Proposed learning requires two operation phase
  - potentiation and depression.
- The spike signals applied to the top electrode (TE) and bottom electrode (BE) are determined according to label data and feature codes.

HRS = High Resistance Rate
LRS = Low Resistance Rate

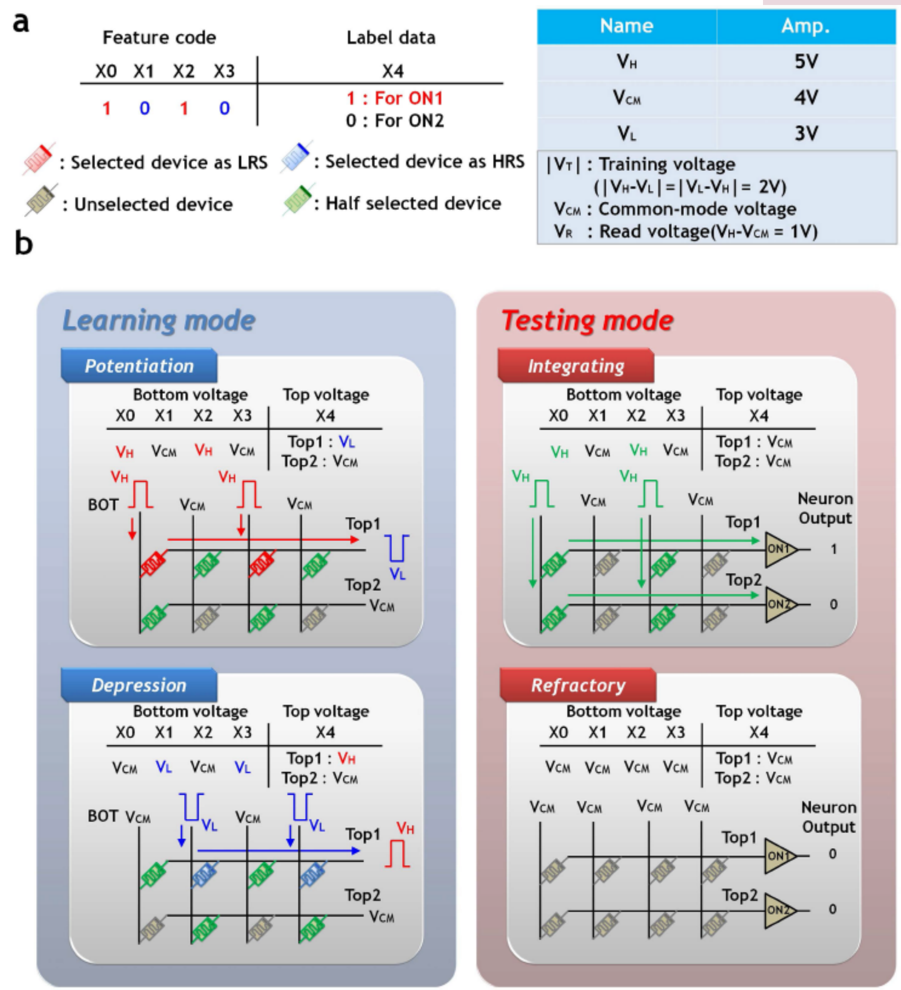


Figure 4. The proposed learning scheme. (a) An example of the feature code and label data to train memristive synapses of top1. (b) A schematic of the 4 pre-neurons and 2 post-neurons HNN according to operation phase.

Memristive HNN Testing and Classification

- In testing mode, applied feature codes to the memristive HNN are recognized by the decision logics based on the output signals of the post-neurons.

- Like the learning mode, the testing mode requires two operation phases, integrating and refractory.

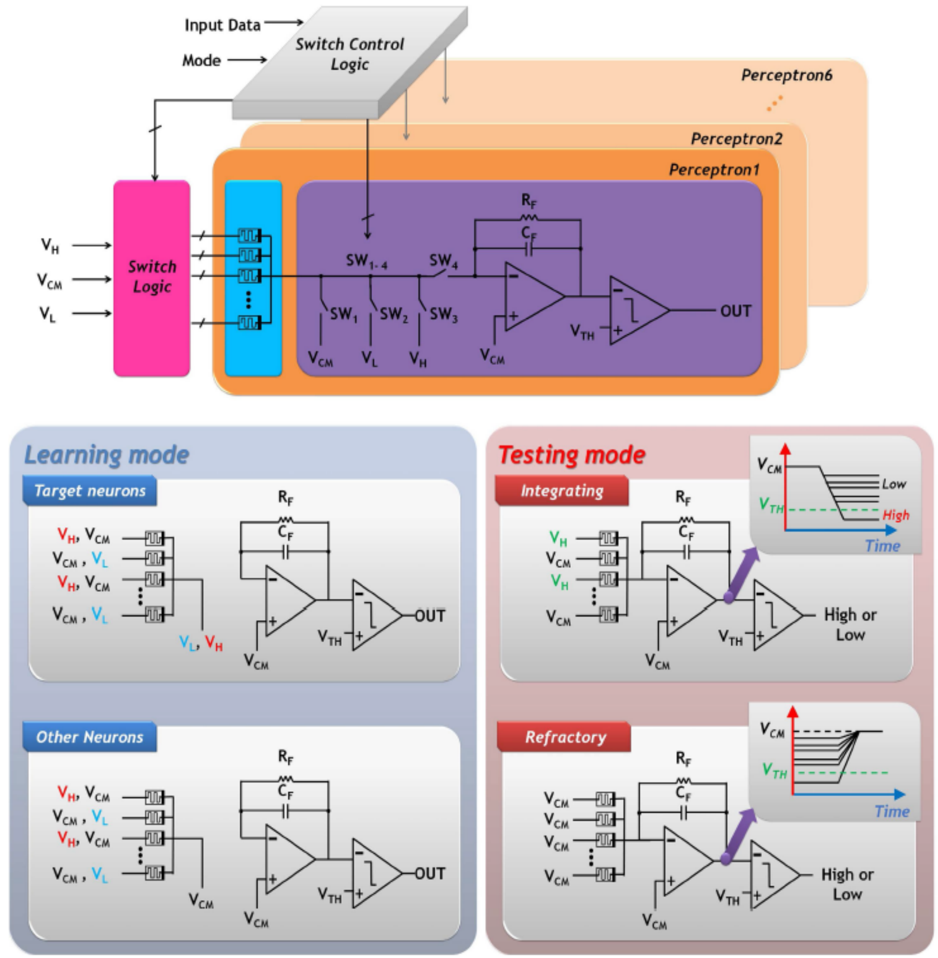


Figure 5. **Circuit Implementation.** The circuit includes a switch array, switch control logic, 32x6 cross-point memristive synapse array and six neuron circuits. Each neuron contains OPAMP based inverting integrator and comparator. Also, a schematic of HNN circuit according to operation phase are shown in this figure.

Memristive HNN Testing and Classification

- Post neuron: leaky integrate-and-fire neuron, including a comparator and inverting leaky integrator
- As soon as the integrator output drops below a neuron's threshold voltage, the comparator output generates a high value and the neuron is assumed to have fired.

- After the integrating phase has completed, the refractory phase starts.
- In refractory phase, the charge on the integration capacitor needs to be fully discharged through the leaky path to prepare the neuron for the next feature code.

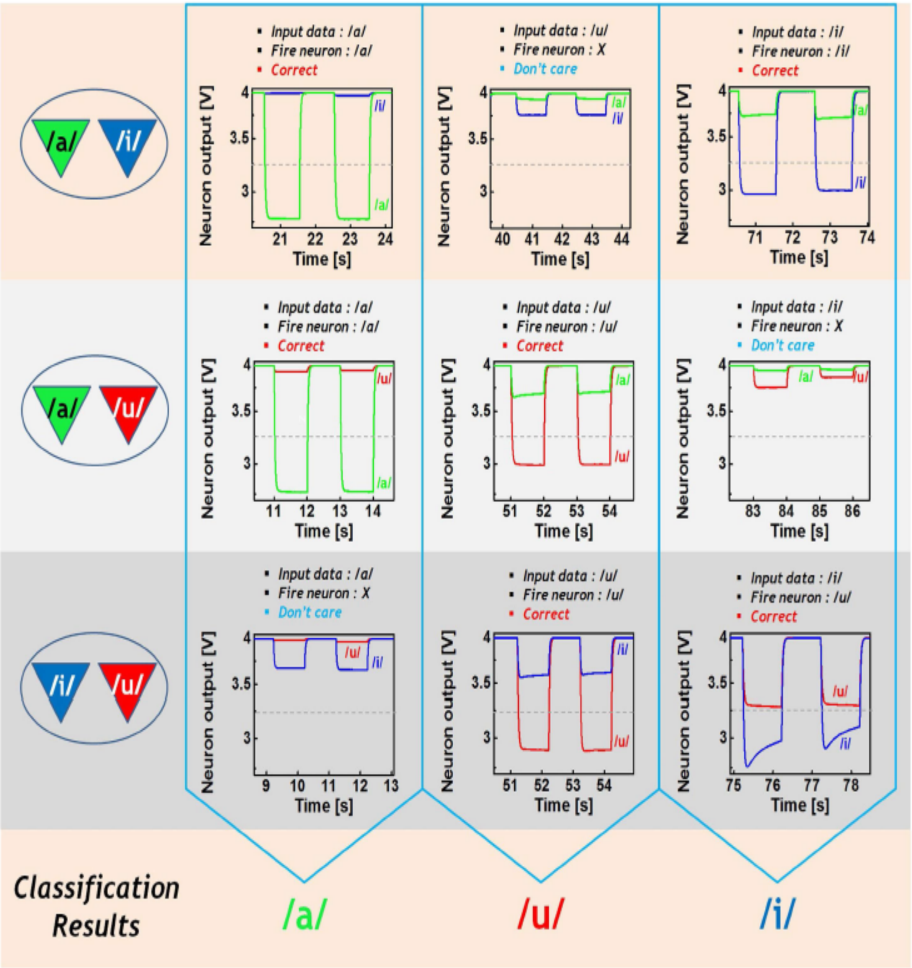
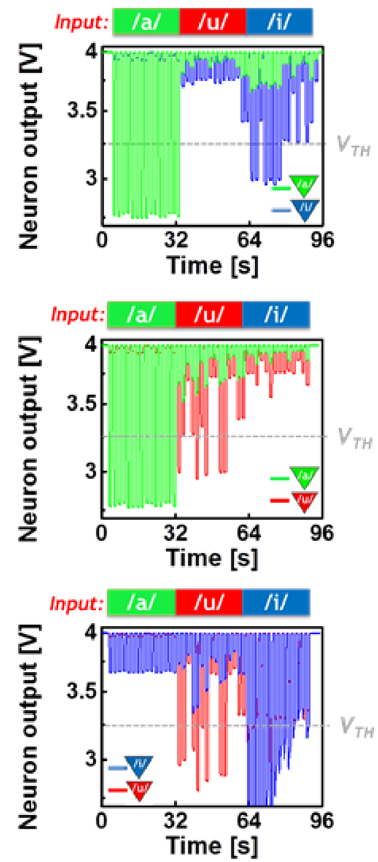


Figure 6. The recognition results of speech imagination. Measured output of each integrator during testing mode is shown. When feature code of /a/ is used as an input of memristive HNN, its results is shown in first column. In the cases of /u/ and /i/, its results are also shown in second and third column, respectively.

Discussion

- The first electronic memristive HNN system for EEG pattern recognition
- Cross-point memristive synapse array using a 200 mm wafer scale
- Impressive classification results with speech imagery data for vowels
- Future direction
  - <u>High density memristive HNN</u>
  - Overcoming the scalability, connectivity, and synaptic density challenges



Supplementary Figure S3 | Classification results for testing. The feature codes of /a/, /u/ and /i/ are sequentially applied to memristive HNN and 15 codes for each feature are used for test. The post-neurons are paired into 3 groups and each group compares two out of vowels, i. e. /a/ vs /i/, /a/ vs/u/ and /i/ vs/u/.

Part II.

Multiclass EEG Discrimination with Speech Imagination (Vowels and Words)

Biomed. Res. Int. (2016) & IEEE Trans. Biomed. Eng. (2018)

Vowel Imagination

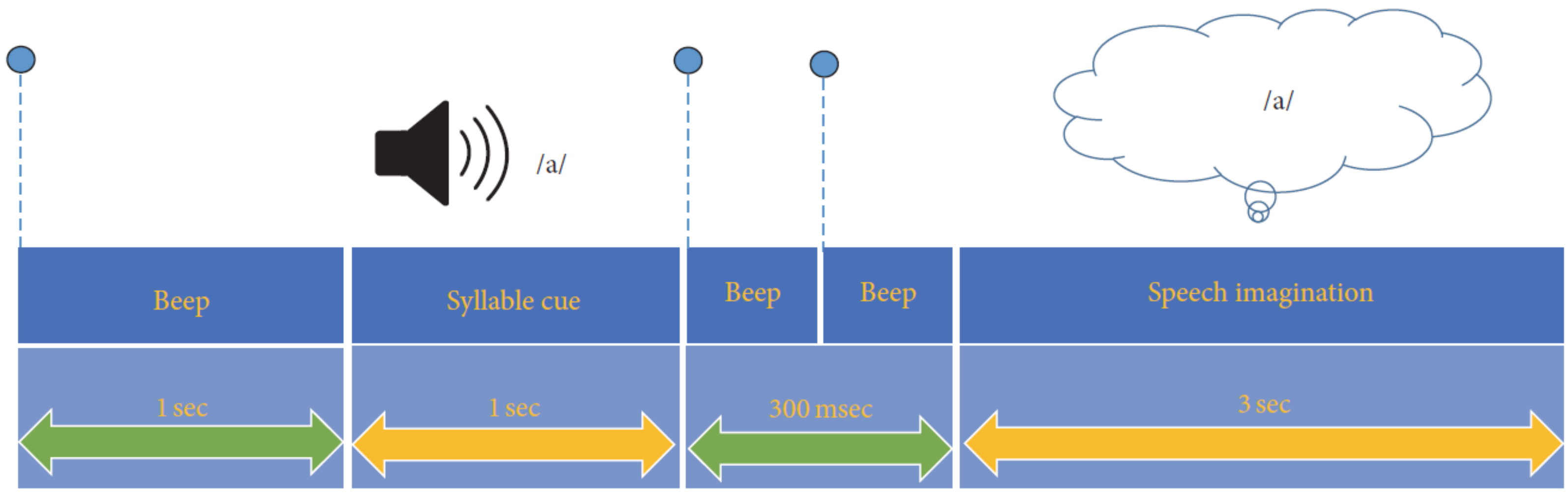
- Vowels: /a/, /e/, /i/, /o/, and /u/ (plus mute)
  - Silent speech BCI?

- Five healthy subjects (5 males; mean age: 28.25 ± 2.71, range: 26-32)
- 5 sessions with 10 trials for each syllable and mute
- Experimental design: e-Prime 2.0 software
- A HydroCel Geodesic Sensor Net with 64 channels
- Net Amps 300 amplifiers (Electrical Geodesics, Inc., Eugene, OR, USA)
  - 1000 Hz sampling rate; 1-100 Hz bandpass-filtered
  - IIR notch filter (Butterworth; order 4; bandwidth 59-61 Hz)

Vowel Imagination

- Data preprocessing
  - 3s epoch
    - 30 time segments with a 0.2s length and 0.1s overlap
    - 6(conditions)×50(trials)×30(blocks) = 9000 samples
  - Features
    - Mean, variance, standard deviation, skewness
    - 4(features)×60(channels) = 240(dimension of feature vector)
  - 10-fold cross-validation
  - LASSO sparse regression model based feature selection

Figure 1



- Syllable cue: vowels /a/, /e/, /i/, /o/, /u/ and mute are randomly presented.
- Beep: beep sound for preparation of listening the sound or covert vowel articulation.
- Speech Imagination: covert vowel articulation (to imagine the vowel).

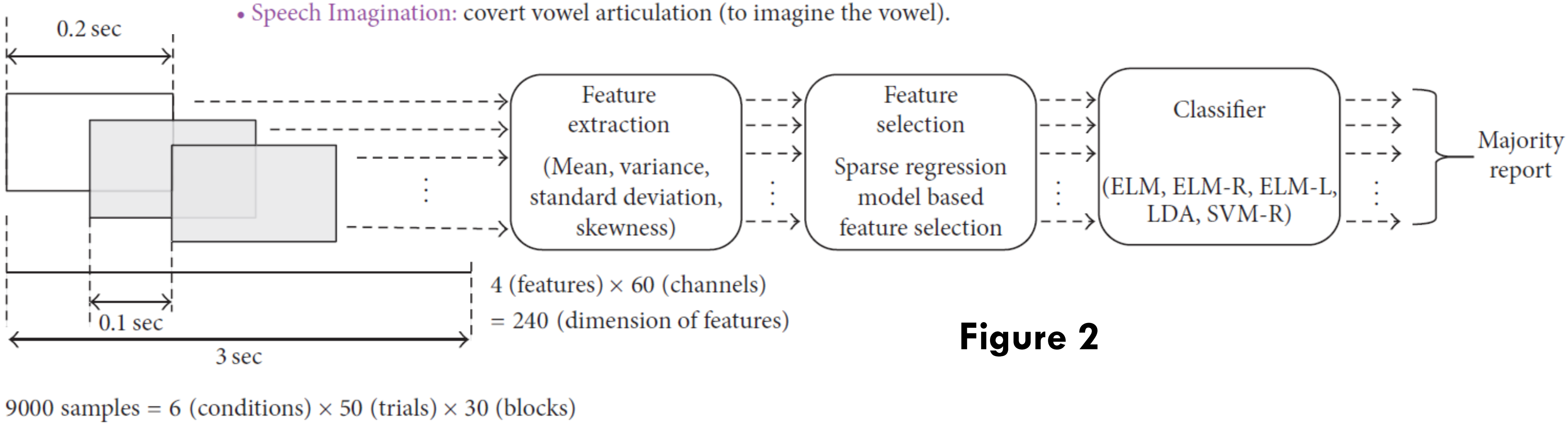


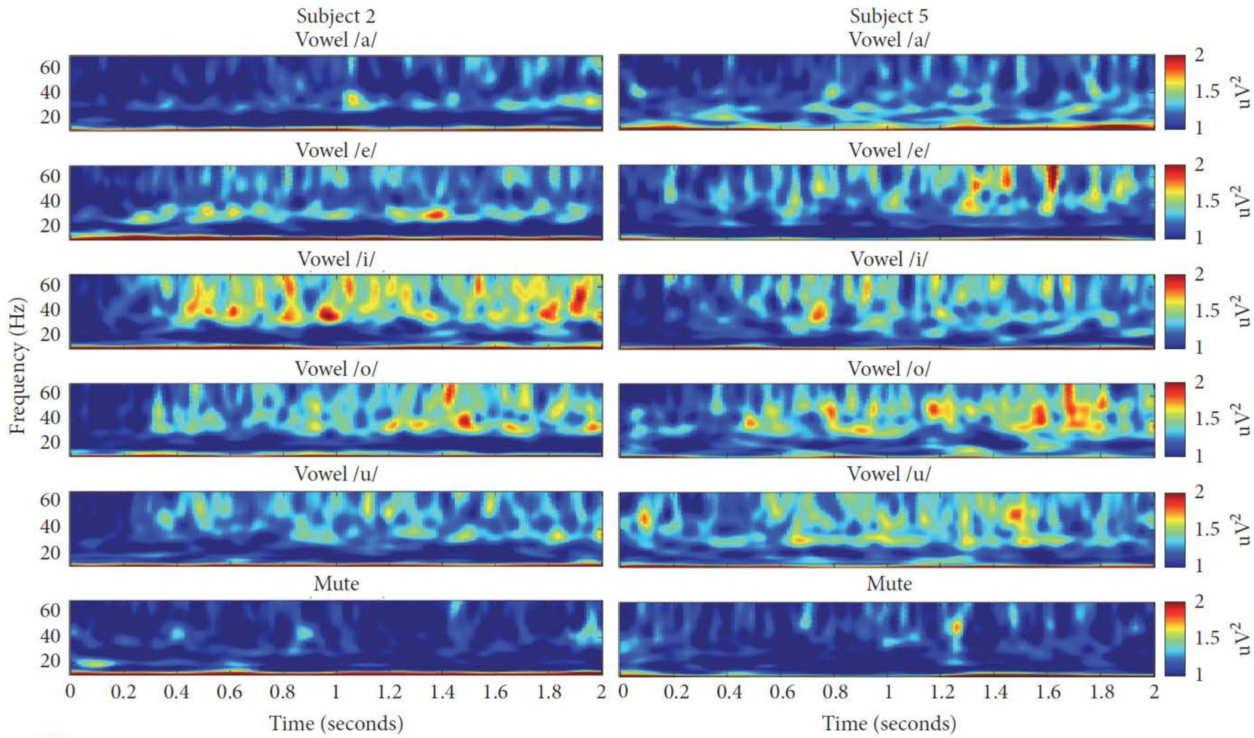
Figure 2

Vowel Imagination

- Classifiers
  - Extreme learning machine (ELM)
    - A type of feedforward neural network
    - High speed and good generalization performance compared to the classic gradient-based learning algorithms
      - Randomly assigned input weights
      - Analytically calculated output weights
    - ELM with linear kernel (ELM-L)
    - ELM with radial basis function (EML-R)

  - Support vector machine with radial basis function (SVM-R)
  - Linear discriminant analysis (LDA)

Figure 3



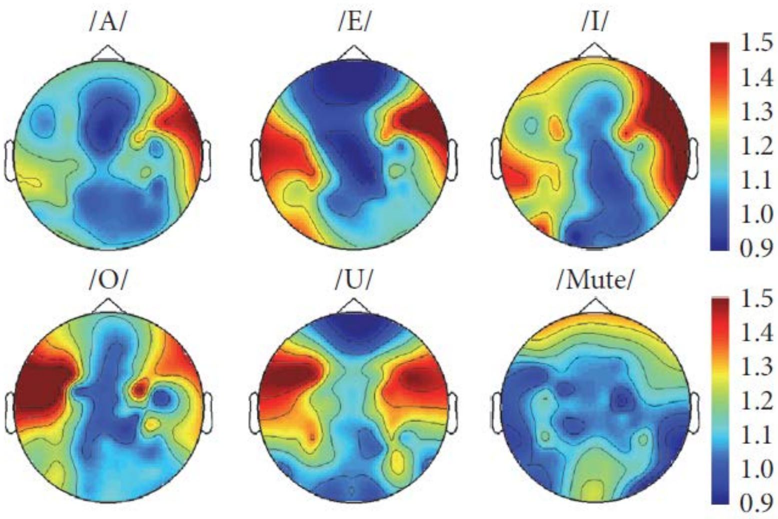


Figure 4

Table 1: Classification accuracies in % employing SVM-R, ELM, ELM-L, ELM-R, and LDA for subject 2. The highest classification accuracy among the four classifiers is marked in bold for pairwise combination. Classification accuracies are expressed as mean and associated standard deviation. SVM-R, ELM, ELM-L, ELM-R, and LDA denote the support vector machine with radial basis function, extreme learning machine, extreme learning machine with a linear kernel, extreme learning machine with a radial basis function, and linear discriminant analysis, respectively.

Classifier	/a/ versus /e/	/a/ versus /i/	/a/ versus /o/	/a/ versus /u/	/e/ versus /i/	/e/ versus /o/	/e/ versus /u/	/i/ versus /o/	/i/ versus /u/	/o/ versus /u/	/a/ versus /mute/	/e/ versus /mute/	/i/ versus /mute/	/o/ versus /mute/	/u/ versus /mute/
SVM-R	50.24 ± 1.01	55.32 ± 2.15	51.41 ± 0.51	50.22 ± 0.60	50.31 ± 0.19	49.18 ± 0.23	52.41 ± 1.57	52.47 ± 0.71	51.11 ± 0.22	51.02 ± 1.32	49.48 ± 0.70	50.35 ± 0.22	51.22 ± 1.22	50.14 ± 1.60	51.23 ± 0.23
ELM	81.41 ± 1.18	94.23 ± 1.02	62.42 ± 2.15	73.34 ± 3.21	**90.55 ± 1.78**	69.76 ± 12.94	56.23 ± 3.48	96.32 ± 0.18	97.47 ± 0.76	66.81 ± 3.83	92.85 ± 2.43	82.31 ± 2.16	**99.41 ± 0.12**	88.16 ± 3.74	80.28 ± 2.87
ELM-L	81.32 ± 0.47	98.15 ± 0.67	67.11 ± 1.04	82.22 ± 2.40	88.31 ± 1.73	78.25 ± 2.23	53.14 ± 3.10	98.16 ± 0.37	**98.23 ± 2.12**	68.36 ± 1.63	92.28 ± 0.83	80.49 ± 3.70	99.12 ± 0.33	93.14 ± 2.21	87.25 ± 1.12
ELM-R	**86.28 ± 1.12**	**99.02 ± 0.76**	**73.03 ± 4.62**	83.14 ± 1.02	89.08 ± 0.14	**78.27 ± 0.16**	**58.36 ± 3.41**	**98.15 ± 0.22**	97.07 ± 1.42	**73.38 ± 2.73**	**95.09 ± 1.03**	**89.28 ± 3.13**	99.01 ± 0.14	**93.25 ± 0.73**	**93.01 ± 1.12**
LDA	79.25 ± 1.62	90.32 ± 2.61	60.57 ± 2.13	**84.12 ± 1.14**	88.23 ± 1.67	70.04 ± 1.43	56.38 ± 1.41	97.07 ± 0.39	96.28 ± 1.62	65.14 ± 1.73	91.26 ± 1.43	80.38 ± 4.70	98.07 ± 1.32	90.39 ± 1.62	82.25 ± 1.27

Table 3: Confusion matrix for all pairwise combinations and subjects using ELM, ELM-L, ELM-R, SVM-R, and LDA.

	Classifiers									
	ELM		ELM-L		ELM-R		SVM-R		LDA	
	Condition positive	Condition negative	Condition positive	Condition negative	Condition positive	Condition negative	Condition positive	Condition negative	Condition positive	Condition positive
Test positive	2516	1234	2649	1101	2635	1115	3675	75	2556	1194
Test negative	1509	2241	1261	2489	1297	2453	3525	225	1398	2352
	Sensitivity = 0.6251	Specificity = 0.6449	Sensitivity = 0.6775	Specificity = 0.6933	Sensitivity = 0.6701	Specificity = 0.6875	Sensitivity = 0.5104	Specificity = 0.7500	Sensitivity = 0.6464	Specificity = 0.6633

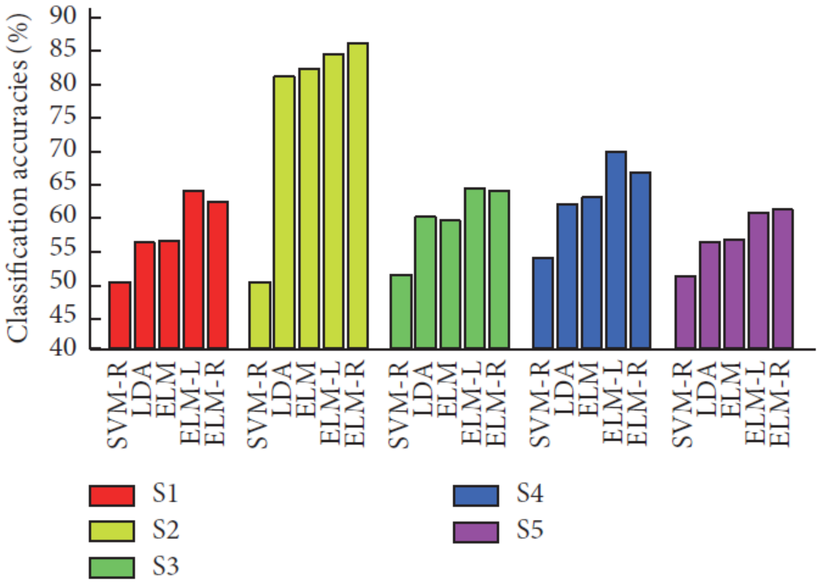


Figure 5

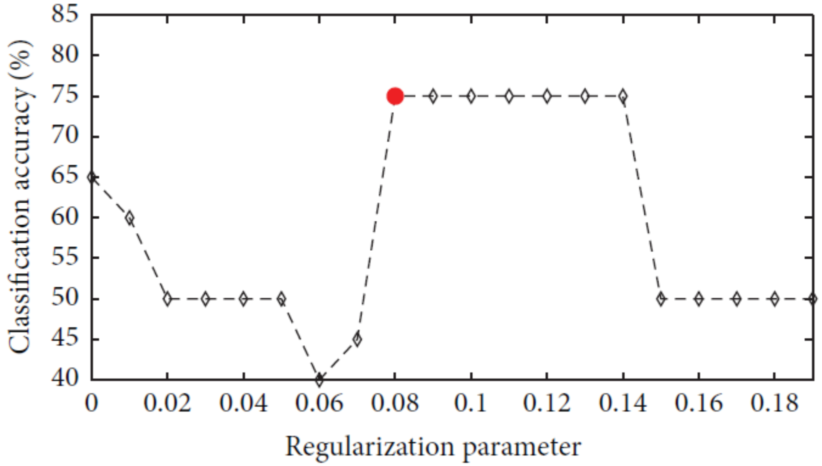
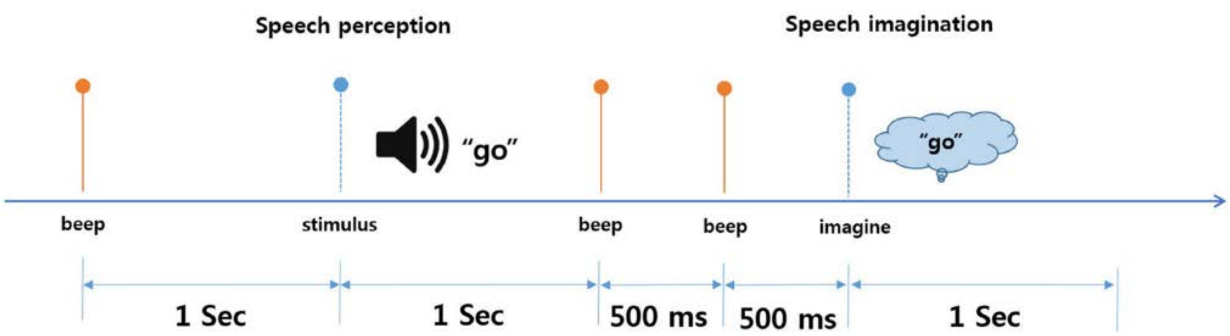


Figure 6

Word Imagination

- Imagined words: 'go', 'back', 'left', 'right', and 'stop'
- Eight healthy Korean Participant (2 women and 6 men, mean age: 27.13 ±3.30; range 22-32)
- 100 EEG responses for each word during three separate sessions.
- Preprocessing
  - 1.5s epochs time-locked to the onset of each task (pre-stimulus: 0.5s)
  - Automatic artifact removal (±100μV), baseline correction with pre-stimulus interval



Word Imagination

- Feature extraction
  - ICA-based artefact removal & time-series reconstruction
  - Four features
    - Covariance Based Features (CF)
    - Maximum Linear Cross-correlation (MaxCOR)
    - Phase-only time-series: Phase-only CF, Phase-only MaxCOR
- Channel selection
  - CS1: left inferior frontal lobe (Broca's Area)
  - CS2: left superior temporal lobe (Wernicke's Area)
  - CS3: CS1 + CS 2
  - CS4: whole brain
- Classifier: ELM (comparison: SVM-L, SVM-RBF, K-NN, Random Forest)

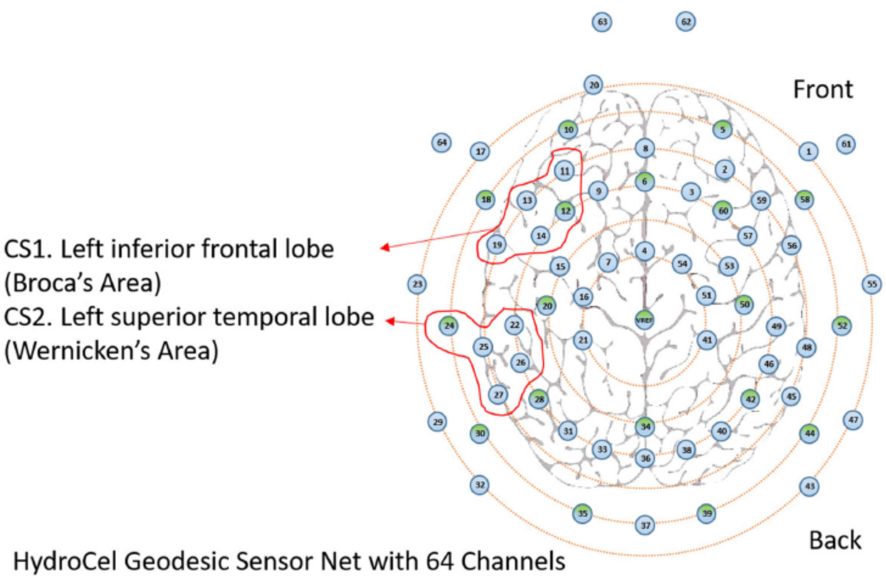


Fig. 2. This figure depicts the EEG electrode locations for the channel selection of Broca's area (CS1) and Wernicke's area (CS2).

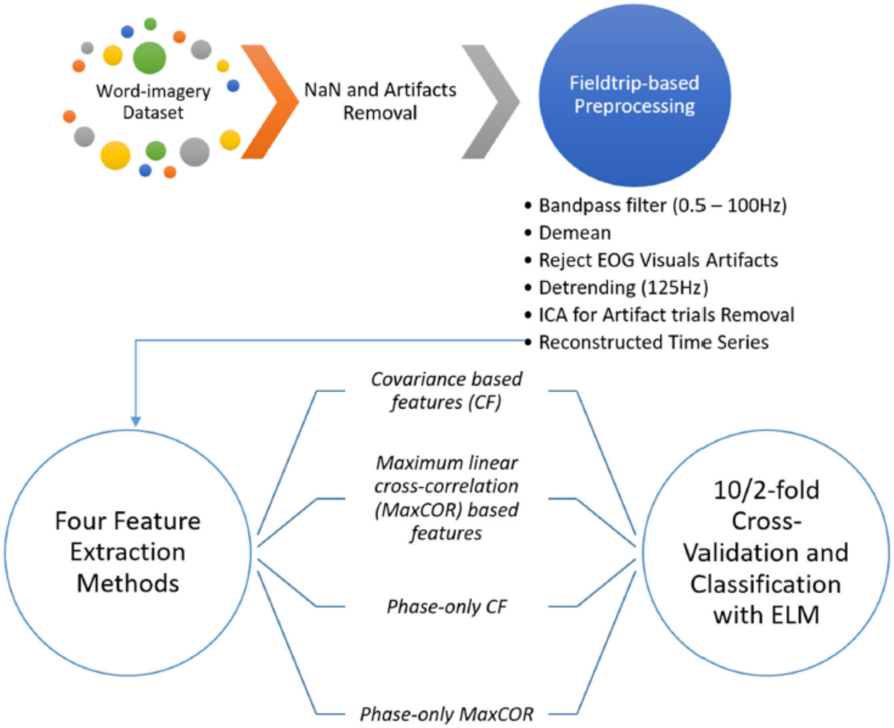
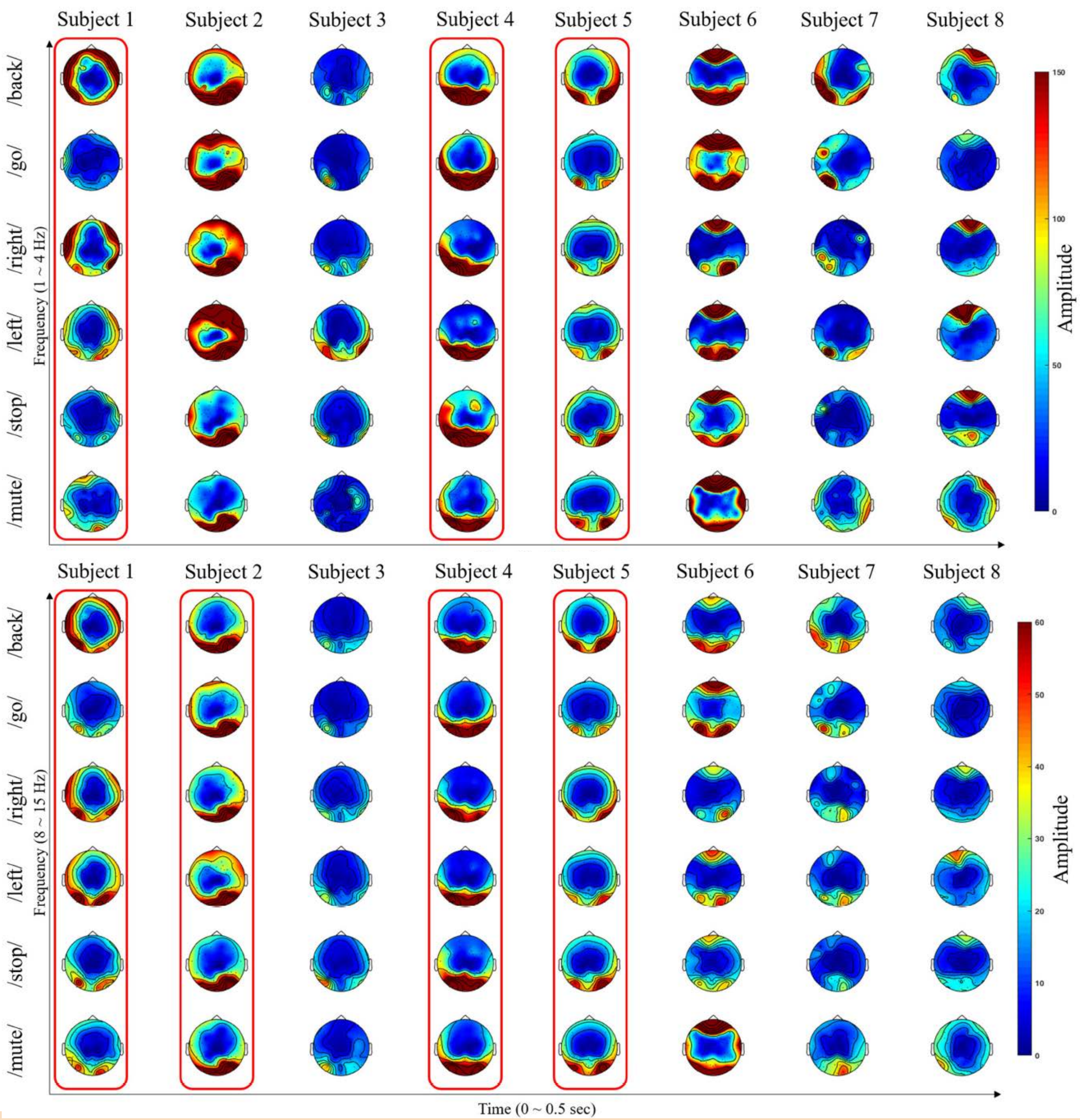


Fig. 3. This figure depicts the overall framework of the study.

Figure 4



(a) delta frequency band

(b) alpha frequency band

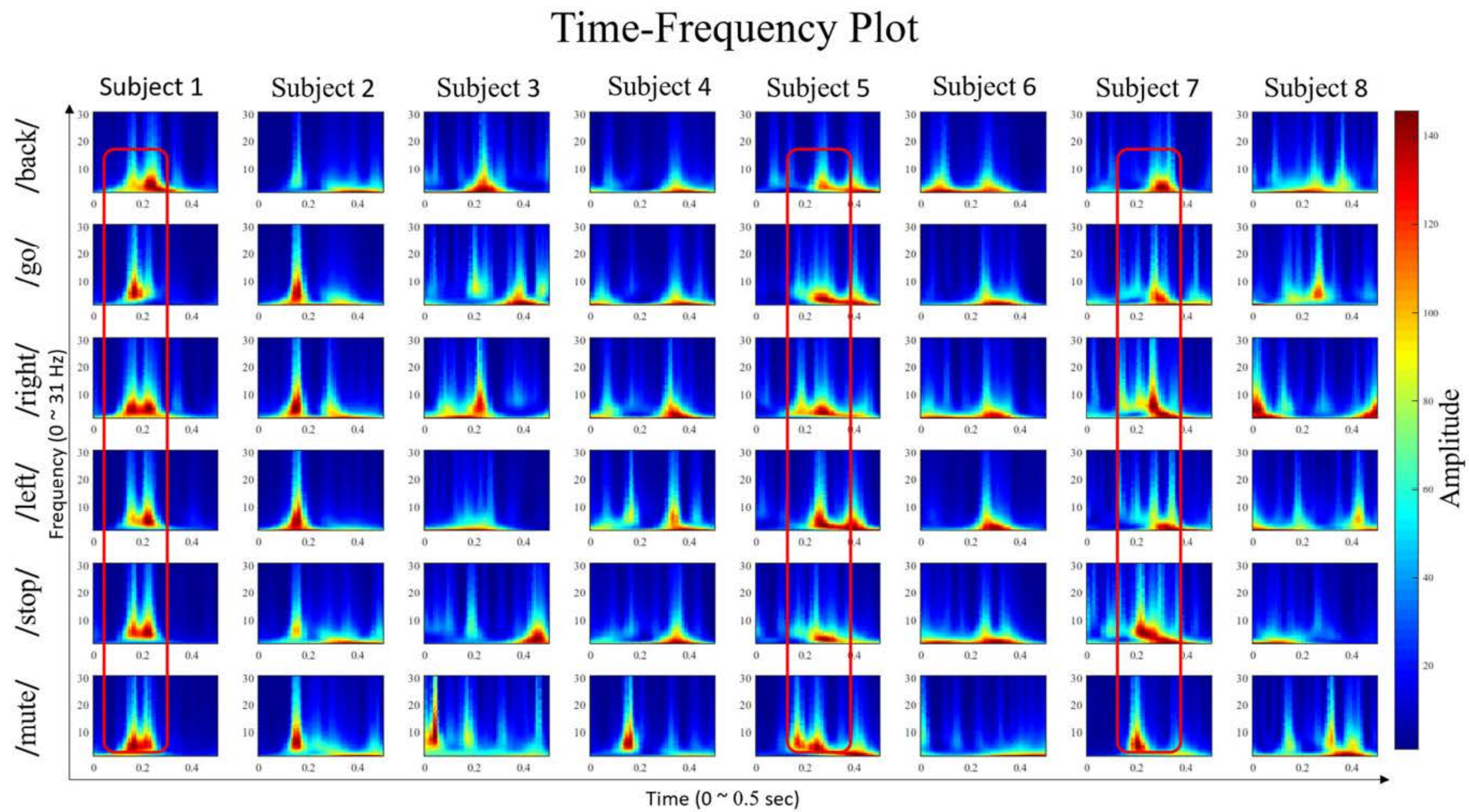


Fig. 5. The time-frequency representation of the word imagination data using the Morlet mother wavelet transform. The frequency range from 0 to 31 Hz was used in the plot for 0.5 s from the onset of imagination stimulation. The trials in the red boxes show potentially similar responses.

TABLE I
MEAN ACCURACY, KAPPA SCORE, AND CORRESPONDING STANDARD DEVIATIONS FOR ALL FOUR FEATURE EXTRACTION METHODS AND CHANNEL SELECTIONS

Subjects	Covariance-Connectivity Features ($Mean \pm SD$)							
	CS1		CS2		CS3		CS4	
	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa
S1	0.352 ± 0.040	0.190 ± 0.050	0.335 ± 0.029	0.169 ± 0.038	0.332 ± 0.042	0.165 ± 0.052	0.358 ± 0.034	0.198 ± 0.043
S2	0.307 ± 0.044	0.132 ± 0.057	0.335 ± 0.047	0.168 ± 0.057	0.336 ± 0.043	0.168 ± 0.054	0.361 ± 0.049	0.201 ± 0.060
S3	0.358 ± 0.041	0.199 ± 0.050	0.352 ± 0.059	0.190 ± 0.073	0.361 ± 0.046	0.202 ± 0.056	0.371 ± 0.030	0.215 ± 0.037
S4	0.326 ± 0.039	0.157 ± 0.049	0.332 ± 0.046	0.164 ± 0.057	0.322 ± 0.038	0.152 ± 0.047	**0.403** ± 0.036	**0.256** ± 0.045
S5	0.358 ± 0.063	0.198 ± 0.076	0.371 ± 0.030	0.215 ± 0.037	0.368 ± 0.055	0.209 ± 0.068	0.394 ± 0.045	0.241 ± 0.057
S6	0.335 ± 0.062	0.170 ± 0.077	0.355 ± 0.026	0.193 ± 0.032	0.342 ± 0.051	0.178 ± 0.064	0.345 ± 0.066	0.180 ± 0.083
S7	0.359 ± 0.058	0.200 ± 0.071	0.333 ± 0.046	0.167 ± 0.058	0.355 ± 0.038	0.194 ± 0.049	0.377 ± 0.029	0.221 ± 0.038
S8	0.349 ± 0.052	0.186 ± 0.064	0.355 ± 0.026	0.193 ± 0.032	0.354 ± 0.044	0.193 ± 0.054	0.364 ± 0.040	0.206 ± 0.048
Average	0.3034	0.179	0.310	0.182	0.307	0.183	0.329	0.215
	Phase-only Covariance-Connectivity Features ($Mean \pm SD$)							
Subjects	CS1		CS2		CS3		CS4	
	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa
S1	0.351 ± 0.041	0.188 ± 0.048	0.348 ± 0.054	0.184 ± 0.067	0.371 ± 0.046	0.213 ± 0.056	0.383 ± 0.046	0.230 ± 0.057
S2	0.349 ± 0.031	0.185 ± 0.038	0.345 ± 0.041	0.182 ± 0.051	0.348 ± 0.056	0.184 ± 0.070	0.373 ± 0.043	0.217 ± 0.054
S3	0.332 ± 0.025	0.165 ± 0.030	0.352 ± 0.051	0.189 ± 0.064	0.325 ± 0.043	0.157 ± 0.054	0.362 ± 0.031	0.202 ± 0.039
S4	0.331 ± 0.037	0.164 ± 0.046	0.348 ± 0.029	0.185 ± 0.037	0.348 ± 0.043	0.187 ± 0.054	0.368 ± 0.040	0.211 ± 0.050
S5	0.345 ± 0.059	0.181 ± 0.074	0.361 ± 0.041	0.201 ± 0.051	0.331 ± 0.067	0.164 ± 0.084	0.355 ± 0.051	0.193 ± 0.063
S6	0.342 ± 0.050	0.176 ± 0.062	0.346 ± 0.061	0.182 ± 0.076	0.339 ± 0.052	0.174 ± 0.063	0.355 ± 0.028	0.194 ± 0.033
S7	0.358 ± 0.040	0.197 ± 0.049	0.358 ± 0.049	0.199 ± 0.061	0.364 ± 0.040	0.205 ± 0.049	0.355 ± 0.036	0.193 ± 0.045
S8	0.358 ± 0.044	0.198 ± 0.054	0.355 ± 0.031	0.194 ± 0.039	0.356 ± 0.050	0.195 ± 0.061	0.345 ± 0.051	0.181 ± 0.065
Average	0.307	0.182	0.314	0.190	0.313	0.185	0.321	0.203

TABLE I

MEAN ACCURACY, KAPPA SCORE, AND CORRESPONDING STANDARD DEVIATIONS FOR ALL FOUR FEATURE EXTRACTION METHODS AND CHANNEL SELECTIONS

Subjects	Covariance-Connectivity Features $(Mean \pm SD)$
S1	
S2	
S3	
S4	
S5	
S6	
S7	
S8	
Average	

	MaxCOR-Connectivity Features $(Mean \pm SD)$							
Subjects	CS1		CS2		CS3		CS4	
	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa
S1	0.361 ± 0.070	0.201 ± 0.088	0.361 ± 0.035	0.201 ± 0.044	0.358 ± 0.031	0.198 ± 0.039	0.375 ± 0.054	0.219 ± 0.068
S2	0.335 ± 0.052	0.169 ± 0.066	0.348 ± 0.055	0.186 ± 0.069	0.349 ± 0.068	0.185 ± 0.085	0.367 ± 0.031	0.208 ± 0.037
S3	0.332 ± 0.053	0.162 ± 0.066	0.340 ± 0.059	0.174 ± 0.074	0.326 ± 0.052	0.156 ± 0.066	0.383 ± 0.043	0.229 ± 0.053
S4	0.352 ± 0.046	0.190 ± 0.057	0.365 ± 0.066	0.205 ± 0.083	0.322 ± 0.052	0.152 ± 0.063	0.377 ± 0.052	0.221 ± 0.066
S5	0.352 ± 0.078	0.189 ± 0.096	0.371 ± 0.037	0.212 ± 0.047	0.370 ± 0.042	0.213 ± 0.052	0.351 ± 0.050	0.189 ± 0.062
S6	0.338 ± 0.058	0.173 ± 0.072	0.368 ± 0.048	0.209 ± 0.060	0.316 ± 0.039	0.145 ± 0.049	0.364 ± 0.030	0.205 ± 0.039
S7	0.300 ± 0.063	0.126 ± 0.079	0.368 ± 0.052	0.211 ± 0.064	0.364 ± 0.034	0.205 ± 0.042	0.336 ± 0.030	0.168 ± 0.038
S8	0.333 ± 0.033	0.166 ± 0.043	0.346 ± 0.042	0.182 ± 0.053	0.306 ± 0.064	0.133 ± 0.081	0.368 ± 0.051	0.209 ± 0.064
Average	0.303	0.172	0.323	0.198	0.305	0.173	0.323	0.206

	Phase-only MaxCOR-Connectivity Features $(Mean \pm SD)$							
Subjects	CS1		CS2		CS3		CS4	
	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa
S1	0.351 ± 0.072	0.189 ± 0.090	0.381 ± 0.025	0.226 ± 0.030	0.361 ± 0.038	0.201 ± 0.047	0.345 ± 0.018	0.181 ± 0.023
S2	0.365 ± 0.049	0.206 ± 0.062	0.377 ± 0.052	0.221 ± 0.065	0.356 ± 0.058	0.194 ± 0.072	0.359 ± 0.052	0.199 ± 0.064
S3	0.340 ± 0.059	0.174 ± 0.074	0.352 ± 0.053	0.190 ± 0.067	0.346 ± 0.057	0.181 ± 0.071	0.352 ± 0.040	0.190 ± 0.050
S4	0.333 ± 0.046	0.164 ± 0.057	0.355 ± 0.063	0.193 ± 0.080	0.326 ± 0.054	0.158 ± 0.069	0.375 ± 0.054	0.218 ± 0.068
S5	0.351 ± 0.043	0.189 ± 0.054	0.354 ± 0.060	0.193 ± 0.075	0.354 ± 0.073	0.192 ± 0.091	0.358 ± 0.027	0.197 ± 0.034
S6	0.313 ± 0.029	0.142 ± 0.035	0.342 ± 0.046	0.177 ± 0.057	0.339 ± 0.051	0.173 ± 0.065	0.359 ± 0.037	0.198 ± 0.045
S7	0.358 ± 0.049	0.198 ± 0.062	0.371 ± 0.061	0.214 ± 0.076	0.332 ± 0.056	0.165 ± 0.069	0.362 ± 0.028	0.201 ± 0.034
S8	0.367 ± 0.041	0.209 ± 0.052	0.339 ± 0.052	0.174 ± 0.065	0.359 ± 0.059	0.197 ± 0.074	0.371 ± 0.033	0.213 ± 0.040
Average	0.312	0.184	0.322	0.199	0.311	0.183	0.321	0.200

TABLE II

Mean Multiclass Accuracy for All Four Feature Extraction Methods and Channel Selections Using Four Popular Classifiers

Subjects	CS1				CS2				CS3				CS4			
	Covariance-Connectivity Features															
	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF
S1	15.20	21.60	22.90	25.20	24.80	19.7	21.30	19.00	22.30	21.00	22.60	20.30	19.40	18.40	21.60	22.90
S2	16.80	20.30	20.00	22.90	17.10	22.30	23.90	21.90	17.40	23.20	25.20	21.30	18.40	20.60	19.40	20.30
S3	15.80	23.20	25.50	24.80	18.40	29.40	16.10	27.70	13.90	24.50	24.20	22.90	21.30	20.00	22.30	21.00
S4	20.00	23.90	23.90	21.30	20.30	22.90	20.60	20.30	20.00	23.50	20.60	20.00	16.80	23.50	23.90	18.70
S5	17.10	22.60	21.30	21.00	22.60	26.10	26.10	24.80	20.30	23.20	24.50	21.90	20.00	24.50	23.90	21.90
S6	20.60	24.80	21.30	22.30	21.60	20.60	23.90	23.50	19.40	21.60	19.70	18.40	17.70	23.90	21.00	17.70
S7	20.30	19.70	19.40	19.40	17.70	19.40	23.20	22.30	17.40	21.60	20.00	19.40	16.50	24.20	24.20	22.30
S8	17.10	18.40	21.00	22.90	18.40	22.90	20.30	24.50	18.40	22.90	23.50	22.30	20.30	21.60	24.80	23.90
	Phase-only Covariance-Connectivity Features															
Subjects	CS1				CS2				CS3				CS4			
	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF
S1	20.30	21.00	21.00	23.20	22.60	22.60	21.30	23.20	18.70	21.30	20.60	20.30	21.90	25.50	20.60	25.20
S2	15.20	20.60	26.80	25.50	21.00	24.20	25.20	21.60	21.90	23.20	18.40	20.00	16.10	23.90	22.90	23.20
S3	21.30	21.30	23.20	21.60	20.30	21.30	22.60	21.90	21.90	21.90	21.60	21.90	19.00	23.90	22.30	21.60
S4	17.70	18.10	19.00	19.40	16.80	18.40	16.50	18.10	18.40	21.90	23.90	22.60	19.40	22.30	21.90	21.00
S5	16.80	23.20	20.00	21.00	16.80	20.30	22.30	19.40	18.40	25.80	23.90	22.30	16.50	23.50	21.60	19.70
S6	19.70	24.20	25.20	25.80	18.40	19.70	18.70	19.40	22.90	24.80	18.10	19.70	17.70	23.90	20.00	21.00
S7	20.30	21.30	23.50	22.60	23.20	**30.30**	23.20	20.60	20.00	21.60	24.20	25.50	20.00	23.50	22.60	21.90
S8	15.50	22.30	24.80	23.50	25.20	24.80	21.90	21.90	21.90	22.30	22.60	23.20	18.70	22.90	22.60	23.20

TABLE II
MEAN MULTICLASS ACCURACY FOR ALL FOUR FEATURE EXTRACTION METHODS AND CHANNEL SELECTIONS USING FOUR POPULAR CLASSIFIERS

Covariance-Connectivity Features

Subjects

S1
S2
S3
S4
S5
S6
S7
S8

MaxCOR-Connectivity Features

Subjects	CS1				CS2				CS3				CS4			
	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF
S1	18.40	21.90	21.90	22.90	19.00	21.30	21.00	22.90	20.30	21.60	25.80	22.30	18.70	23.50	20.60	21.60
S2	24.50	22.90	21.00	24.80	18.40	23.50	21.60	20.60	21.30	23.20	18.40	21.60	20.60	23.50	20.30	20.30
S3	18.10	21.00	22.30	21.00	20.60	22.60	21.00	21.60	18.10	21.90	20.60	22.30	20.30	22.60	21.60	20.30
S4	17.70	22.60	22.60	21.90	16.80	18.40	16.50	18.10	18.40	21.90	23.90	22.60	19.40	22.30	21.90	21.00
S5	20.00	21.90	20.00	20.00	18.10	22.90	19.70	20.00	15.80	20.60	22.90	18.70	18.70	20.30	21.00	21.30
S6	25.20	25.50	24.20	20.30	13.90	20.60	19.00	19.00	16.50	21.00	21.90	18.10	21.60	21.90	22.90	23.50
S7	21.60	20.60	21.30	21.00	16.80	25.80	22.60	21.00	19.40	22.60	22.30	21.90	18.70	22.30	23.90	21.60
S8	17.10	21.60	21.60	21.60	17.10	21.60	21.00	21.90	17.10	23.90	22.90	20.60	18.40	23.90	23.50	21.30

Subjects

S1
S2
S3
S4
S5
S6
S7
S8

Phase-only MaxCOR-Connectivity Features

Subjects	CS1				CS2				CS3				CS4			
	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF	SVM-L	RF	K-NN	SVM-RBF
S1	21.30	21.00	22.60	19.70	20.00	24.20	21.90	22.30	15.50	20.00	22.60	18.10	21.60	23.90	24.80	22.60
S2	18.40	24.20	27.10	27.70	20.60	28.10	26.10	23.90	20.30	23.20	20.60	22.90	21.30	20.00	22.30	21.00
S3	22.30	26.50	19.70	22.60	19.40	26.50	18.10	19.70	17.40	19.40	19.00	17.70	14.80	20.30	23.90	20.60
S4	19.70	17.40	21.30	17.70	15.80	21.60	19.70	21.60	20.00	23.20	20.00	22.60	15.80	21.90	20.00	21.00
S5	22.30	22.90	22.30	22.90	15.20	22.30	21.60	22.30	19.00	25.50	22.60	21.90	19.40	21.90	24.20	23.20
S6	22.90	22.60	21.60	20.60	15.50	25.20	25.20	21.00	19.00	21.30	19.00	19.00	19.00	21.90	17.40	19.70
S7	14.80	23.20	22.90	22.90	16.50	22.60	19.70	18.70	18.10	21.30	25.20	21.30	22.60	27.40	27.70	26.50
S8	21.90	22.60	18.40	22.30	17.70	23.90	23.50	24.20	24.80	23.50	22.90	23.50	20.30	24.20	22.30	23.50

Abbreviation: CS = Channel Selection; SVM = support vector machine; L = linear; RF = random forest; K-NN = K-nearest neighbours; RBF = radial basis function

TABLE III

Mean Accuracy and Corresponding Standard Deviations for All the Four Feature Extraction Methods and Channel Selections

	Covariance-Connectivity Features $(Mean \pm SD)$				Phase-only Covariance-Connectivity Features $(Mean \pm SD)$			
Subjects	CS1	CS2	CS3	CS4	CS1	CS2	CS3	CS4
S1	0.831 ± 0.060	0.814 ± 0.079	0.791 ± 0.065	0.838 ± 0.054	0.856 ± 0.080	0.831 ± 0.055	0.823 ± 0.049	0.856 ± 0.079
S2	0.823 ± 0.072	0.806 ± 0.071	0.791 ± 0.011	0.855 ± 0.049	0.824 ± 0.080	0.821 ± 0.066	0.832 ± 0.067	0.839 ± 0.035
S3	0.831 ± 0.086	0.800 ± 0.072	0.790 ± 0.059	0.839 ± 0.075	0.845 ± 0.074	0.856 ± 0.071	0.822 ± 0.077	0.840 ± 0.061
S4	0.824 ± 0.044	0.807 ± 0.039	0.790 ± 0.069	0.857 ± 0.076	0.821 ± 0.103	0.832 ± 0.076	0.831 ± 0.057	0.848 ± 0.097
S5	0.829 ± 0.092	0.807 ± 0.075	0.791 ± 0.063	0.841 ± 0.086	0.863 ± 0.052	0.807 ± 0.037	0.832 ± 0.086	0.831 ± 0.079
S6	0.813 ± 0.082	0.806 ± 0.041	0.789 ± 0.070	$\mathbf{0.879} \pm 0.079$	0.815 ± 0.054	0.839 ± 0.064	0.809 ± 0.073	0.840 ± 0.093
S7	0.816 ± 0.057	0.814 ± 0.087	0.798 ± 0.059	0.839 ± 0.070	0.840 ± 0.079	0.838 ± 0.064	0.833 ± 0.089	0.838 ± 0.056
S8	0.814 ± 0.056	0.798 ± 0.041	0.790 ± 0.057	0.840 ± 0.063	0.816 ± 0.070	0.847 ± 0.059	0.824 ± 0.081	0.831 ± 0.068
Average	0.823	0.807	0.791	0.848	0.835	0.834	0.826	0.840
	MaxCOR-Connectivity Features $(Mean \pm SD)$				Phase-only MaxCOR-Connectivity Features $(Mean \pm SD)$			
Subjects	CS1	CS2	CS3	CS4	CS1	CS2	CS3	CS4
S1	0.831 ± 0.077	0.824 ± 0.057	0.809 ± 0.105	0.840 ± 0.073	0.830 ± 0.073	0.831 ± 0.069	0.831 ± 0.077	0.840 ± 0.049
S2	0.799 ± 0.056	0.840 ± 0.106	0.855 ± 0.073	0.847 ± 0.081	0.830 ± 0.079	0.822 ± 0.064	0.832 ± 0.039	0.855 ± 0.063
S3	0.785 ± 0.127	0.848 ± 0.069	0.822 ± 0.075	0.833 ± 0.091	0.816 ± 0.063	0.824 ± 0.066	0.822 ± 0.076	0.833 ± 0.084
S4	0.806 ± 0.077	0.824 ± 0.095	0.790 ± 0.059	0.840 ± 0.079	0.832 ± 0.087	0.838 ± 0.099	0.806 ± 0.086	0.864 ± 0.064
S5	0.824 ± 0.078	0.855 ± 0.093	0.815 ± 0.065	0.822 ± 0.065	0.837 ± 0.088	0.831 ± 0.058	0.814 ± 0.096	0.847 ± 0.057
S6	0.808 ± 0.104	0.814 ± 0.090	0.824 ± 0.070	0.840 ± 0.062	0.824 ± 0.071	0.816 ± 0.072	0.815 ± 0.064	0.863 ± 0.085
S7	0.816 ± 0.057	0.830 ± 0.061	0.840 ± 0.070	0.871 ± 0.078	0.832 ± 0.086	0.839 ± 0.064	0.838 ± 0.086	0.847 ± 0.047
S8	0.797 ± 0.114	0.831 ± 0.043	0.799 ± 0.065	0.856 ± 0.062	0.846 ± 0.060	0.840 ± 0.090	0.823 ± 0.061	0.832 ± 0.087
Average	0.808	0.833	0.819	0.844	0.831	0.830	0.823	0.848

Abbreviation: CS = Channel Selection

TABLE IV

ESTIMATES OF THE P-VALUE WITH PAIRED T-TEST FOR MULTICLASS AND BINARY ACCURACIES WITH FOUR CHANNEL SELECTIONS

Estimates of p-value from Multiclass Classification Result Through Paired t-Test					
Feature Type	CS1 vs. CS2	CS1 vs. CS3	CS1 vs. CS4	CS2 vs. CS3	CS3 vs. CS4
CF	0.0328	0.2662	0.0074	0.4754	0.0104
Po-CF	0.0725	0.3212	0.0181	0.2750	0.0232
MaxCOR	0.0140	0.4650	0.0008	0.0197	0.0364
Po-MaxCOR	0.0593	0.4563	0.0571	0.0532	0.0466
Estimates of p-value from Binary Classification Results using the Paired t-Test					
Feature Type	CS1 vs. CS2	CS1 vs. CS3	CS1 vs. CS4	CS2 vs. CS3	CS3 vs. CS4
CF	0.0006	0.0001	0.0033	0.0001	0.0001
Po-CF	0.4566	0.0921	0.2291	0.1478	0.0063
MaxCOR	0.3857	0.0683	0.0111	0.0788	0.0042
Po-MaxCOR	0.0073	0.1455	0.0013	0.0608	0.0084

Abbreviation: CS = Channel Selection

Part III.

Future Study Direction

Future Research Direction

- Clinical Application
  - Neurorehabilitation for aphasia patients combined with brain stimulation (tDCS, TMS)
  - Language training for language disorder patients

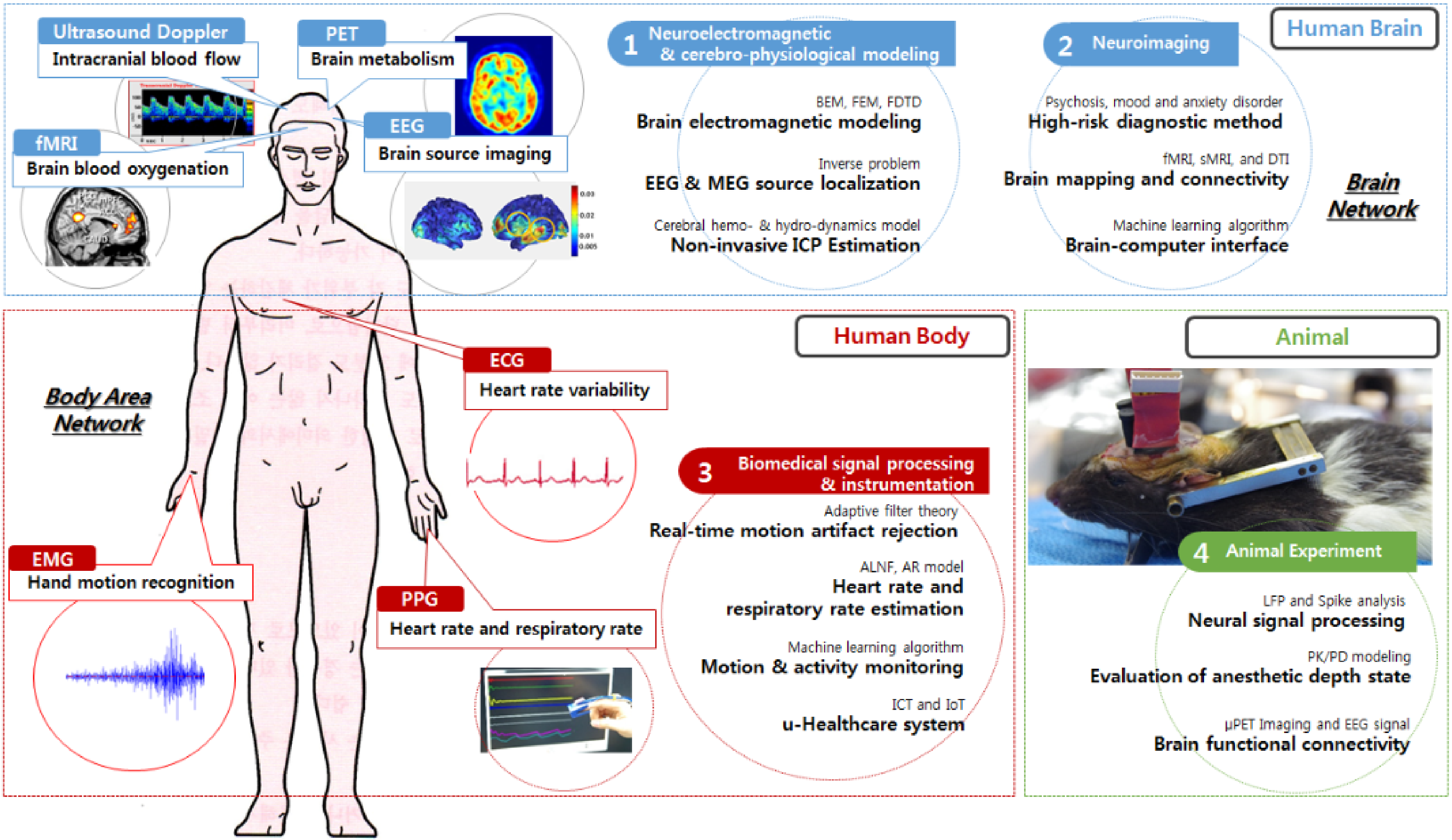
- Brain Computer Interface
  - Silent speech BCI
  - Combination with other paradigm (e.g., motor imagery, P300 speller)

- Collaborate with Language Processing Research

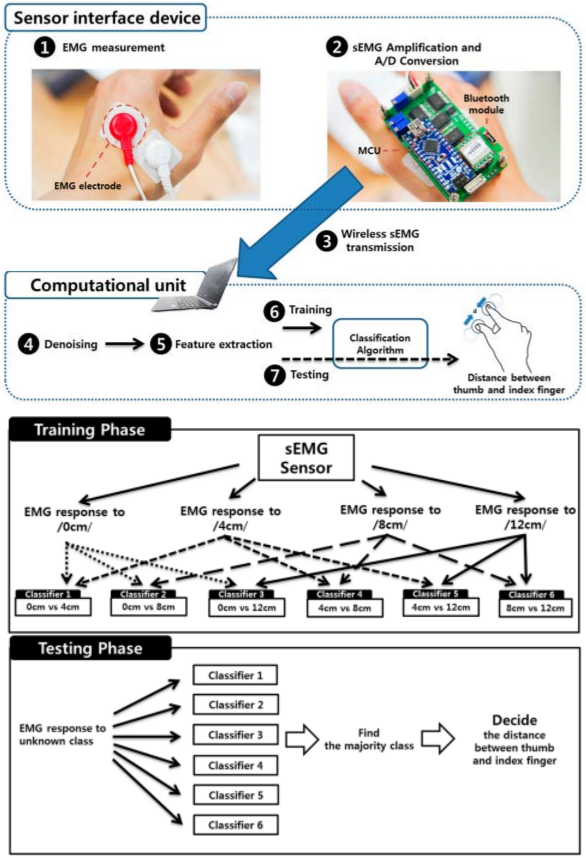
- Collaborate with Neuromorphic & Deep Neural Network Research

Part IV.

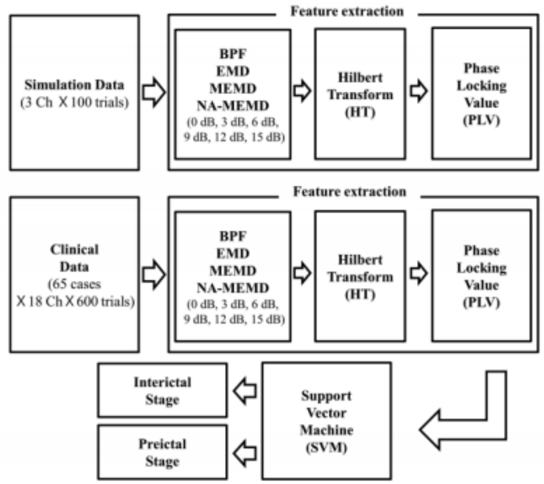
My Lab (BMSSA) & Other Researches

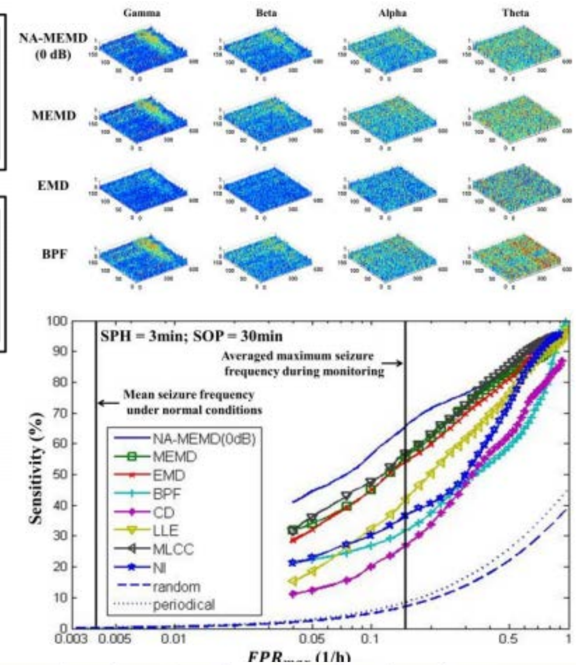

Ultrasound Doppler
Intracranial blood flow
PET
Brain metabolism
fMRI
Brain blood oxygenation
EEG
Brain source imaging
1 Neuroelectromagnetic & cerebro-physiological modeling
BEM, FEM, FDTD
Brain electromagnetic modeling
Inverse problem
EEG & MEG source localization
Cerebral hemo- & hydro-dynamics model
Non-invasive ICP Estimation
2 Neuroimaging
Psychosis, mood and anxiety disorder
High-risk diagnostic method
fMRI, sMRI, and DTI
Brain mapping and connectivity
Machine learning algorithm
Brain-computer interface
Human Brain
Brain Network
Human Body
Body Area Network
ECG
Heart rate variability
EMG
Hand motion recognition
PPG
Heart rate and respiratory rate
3 Biomedical signal processing & instrumentation
Adaptive filter theory
Real-time motion artifact rejection
ALNF, AR model
Heart rate and respiratory rate estimation
Machine learning algorithm
Motion & activity monitoring
ICT and IoT
u-Healthcare system
Animal
4 Animal Experiment
LFP and Spike analysis
Neural signal processing
PK/PD modeling
Evaluation of anesthetic depth state
μPET Imaging and EEG signal
Brain functional connectivity

Other Research Fields

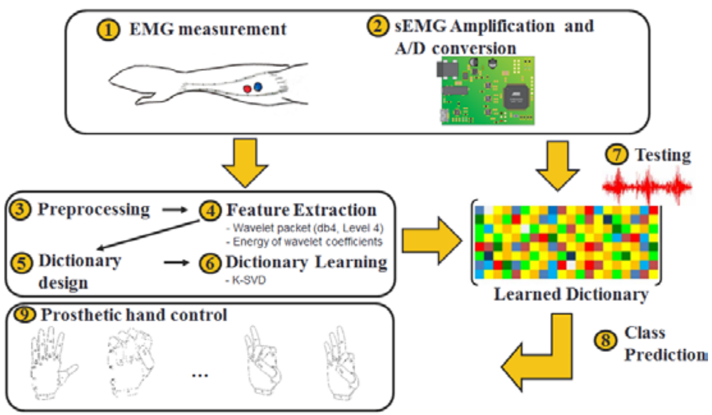


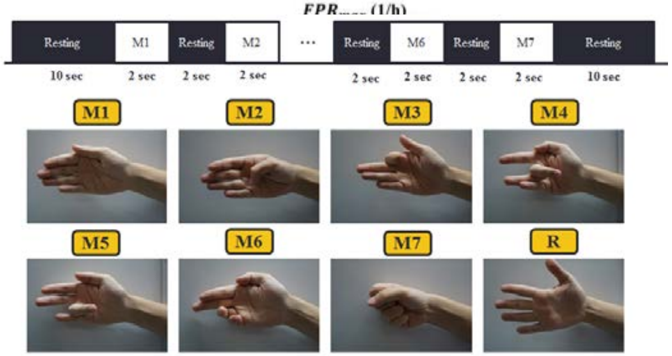
EMG-Based Pinch-to-Zoom HCI



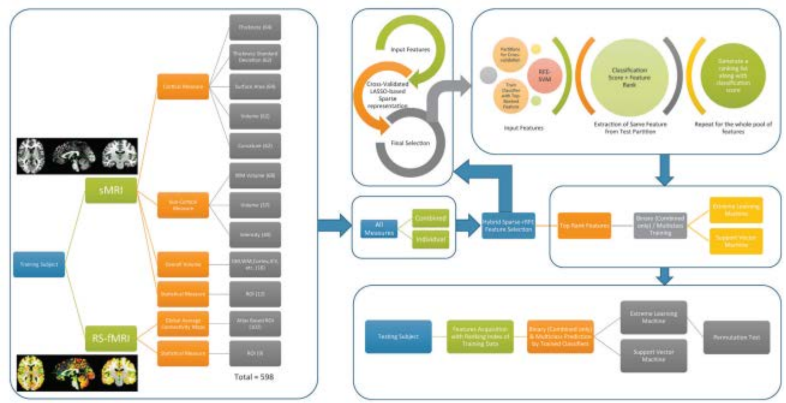


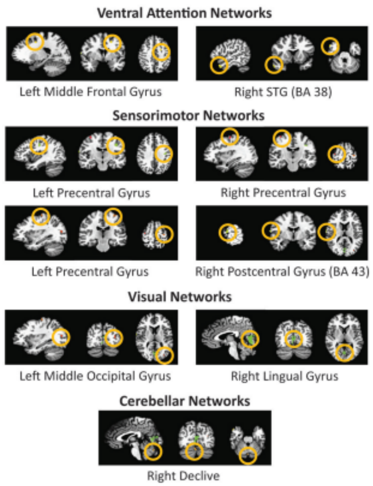
EEG-Based Epilepsy Prediction



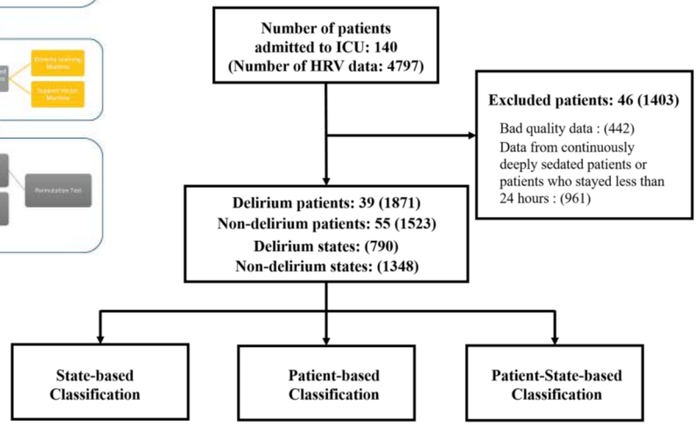


EMG-Based Prosthetic Hand Control

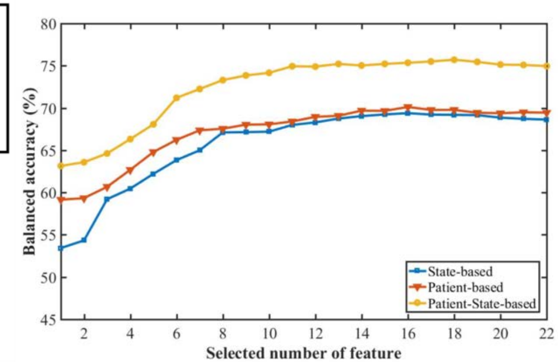


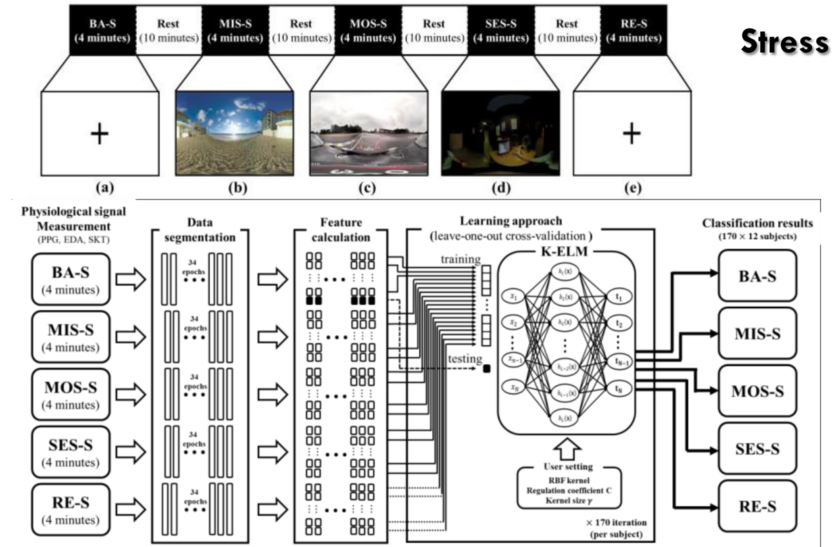


ADHD Discrimination with ELM using sMRI and fMRI

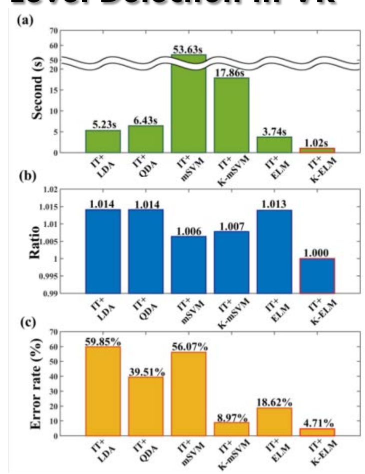


HRV-Based Delirium Prediction



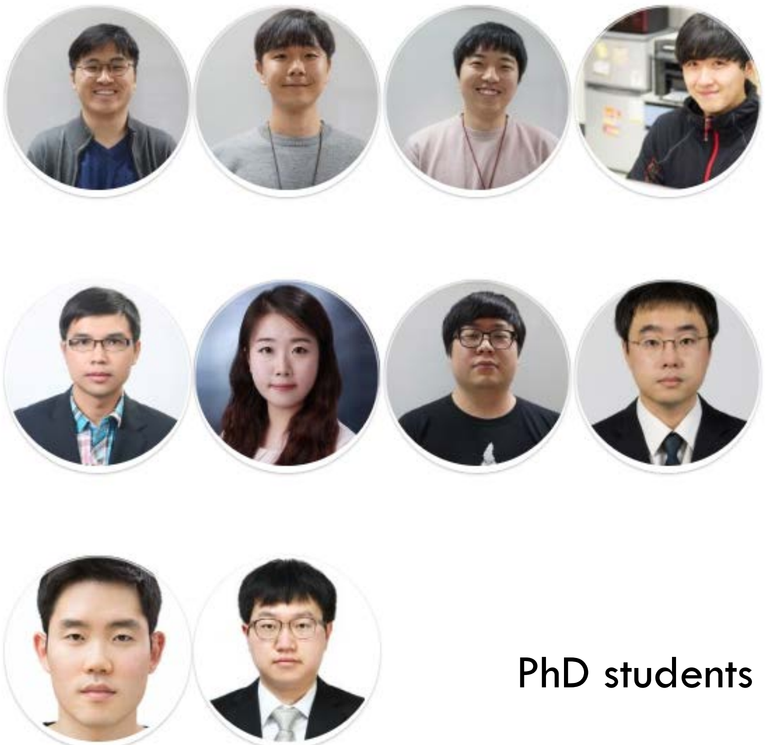


Stress Level Detection in VR

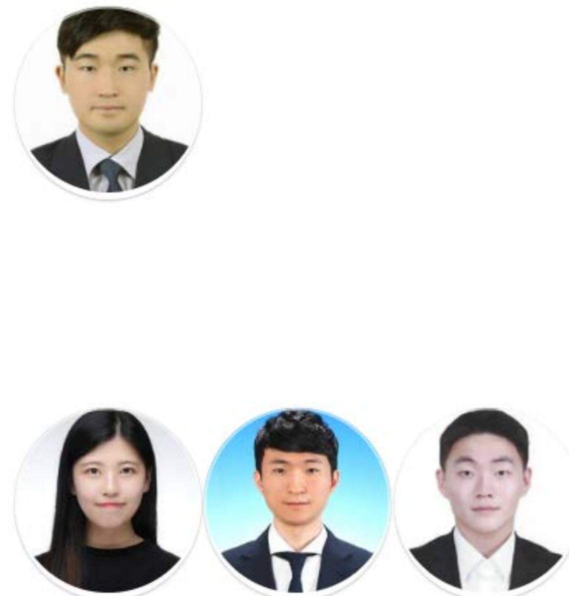


Homepage: https://bmssa.gist.ac.kr/

Current



PhD students



MS students

Alumni

Visiting Scholar

PhD

Thank you !