Single-trial classification of vowel speech imagery using common spatial patterns

C.S. DaSalla, H. Kambara, M. Sato, Y. Koike

(2009)

Presented by Peter Hamilton

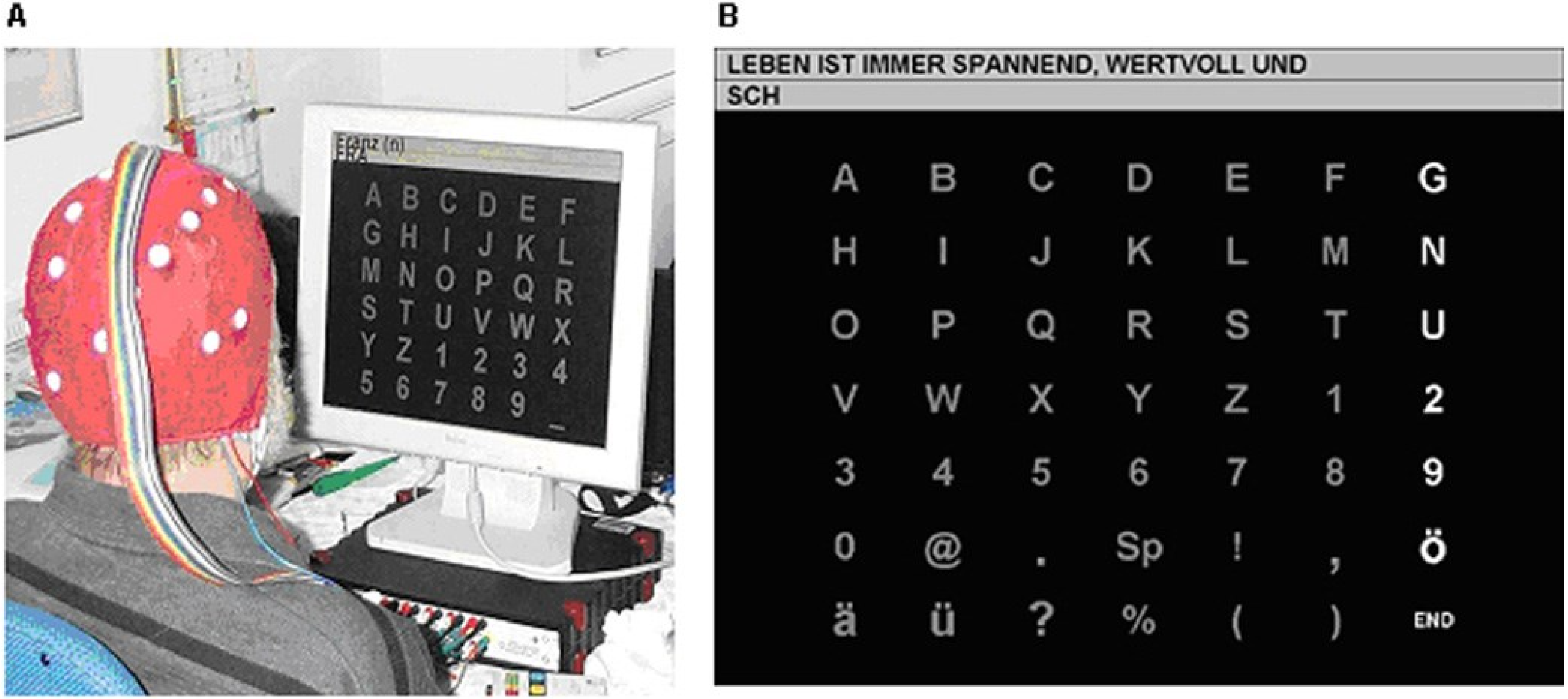
Brain-Computer [illegible]faces (BCI)

Related Work

A communication means for totally locked-in ALS patients based on changes in cerebral blood volume measured with near-infrared light (2007)

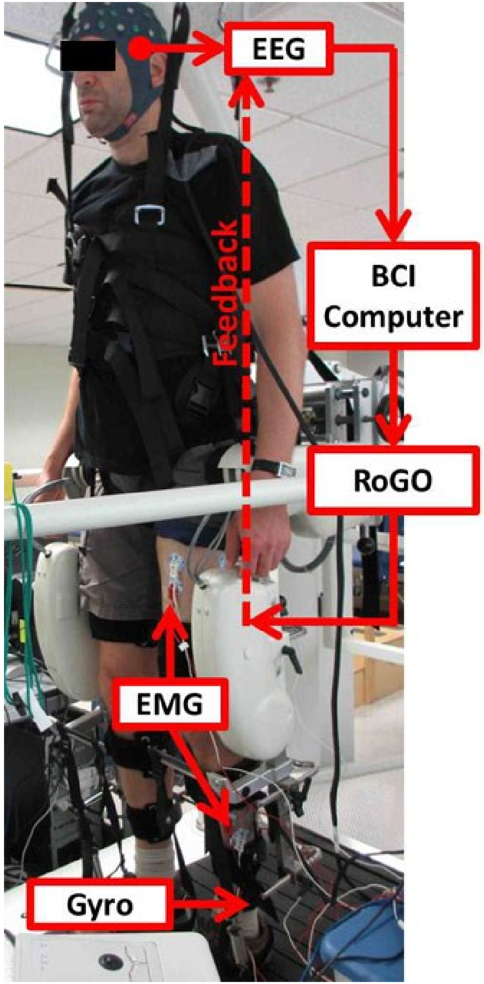
- ‘Yes’ or ‘No’
- Blood Volume(Near-Infared Light)
- +30second latency
- 80% accuracy

A P300-based brain–computer interface for people with amyotrophic lateral sclerosis (2008)



Motor Control

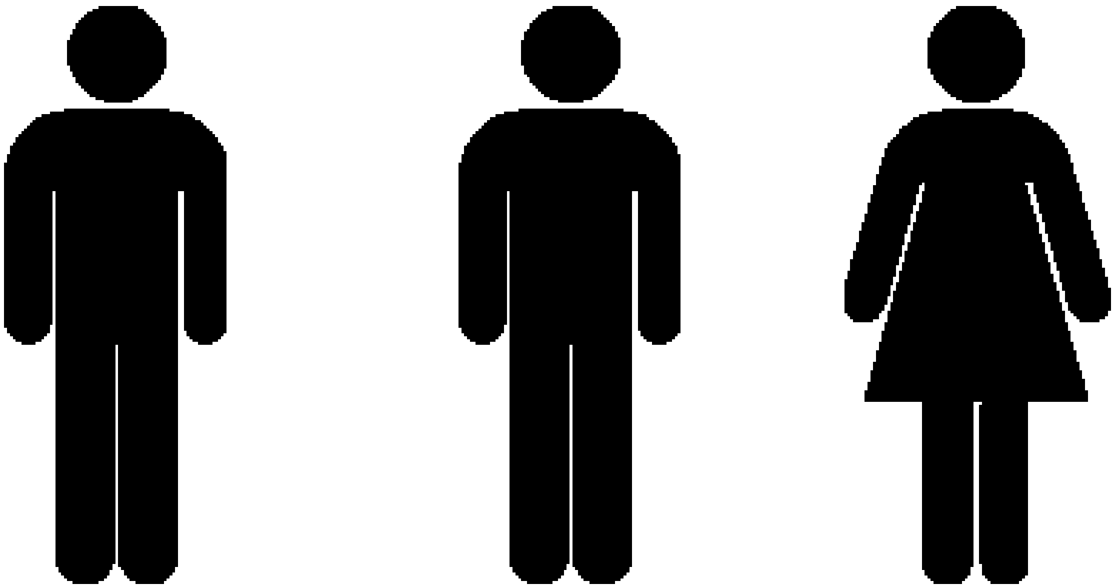
- (2001) Motor imagery and direct brain-computer communication
- Recent Developments
  - Robotic Gait Orthosis (RoGO)



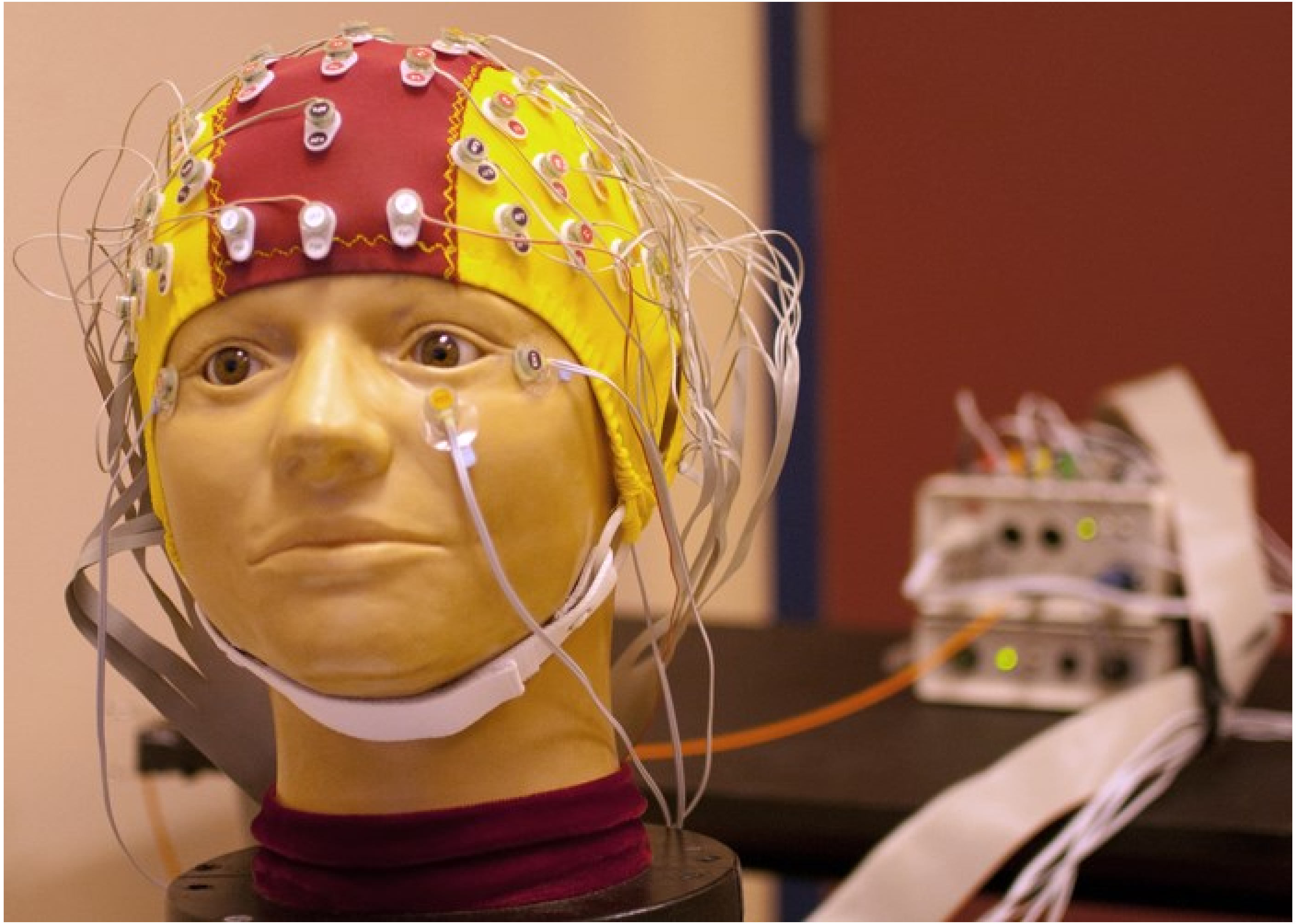
Vowel Brain Activation

- (2000) Single-sweep EEG analysis of neural processes underlying perception and production of vowels
- (1994) Event-related potentials in silent speech

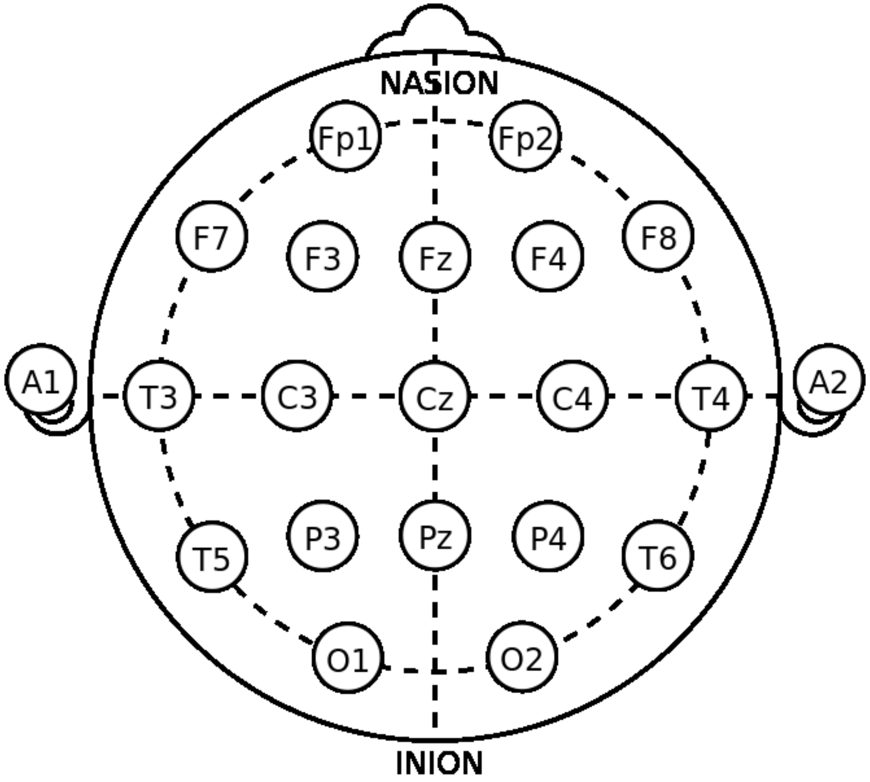
Experiment



Age: 26-29
Right Handed (Edinburgh Inventory)
Fluent in English



International 10-20 System



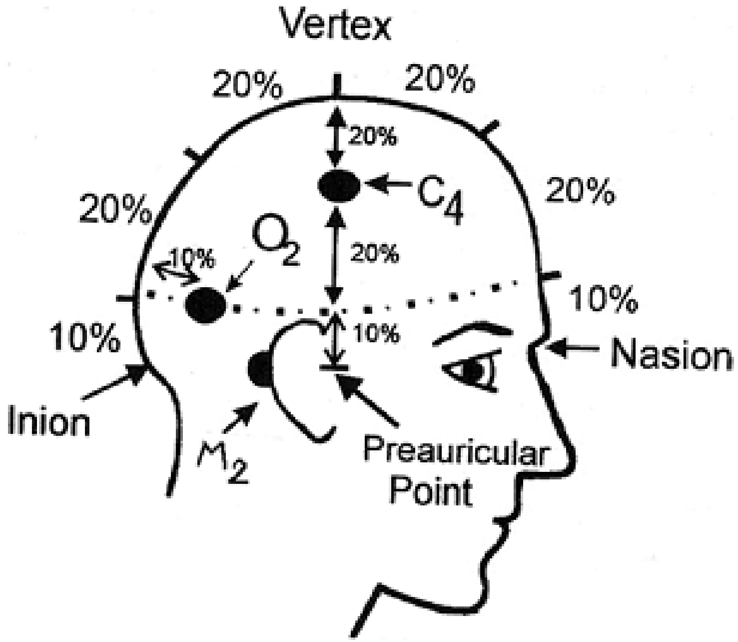
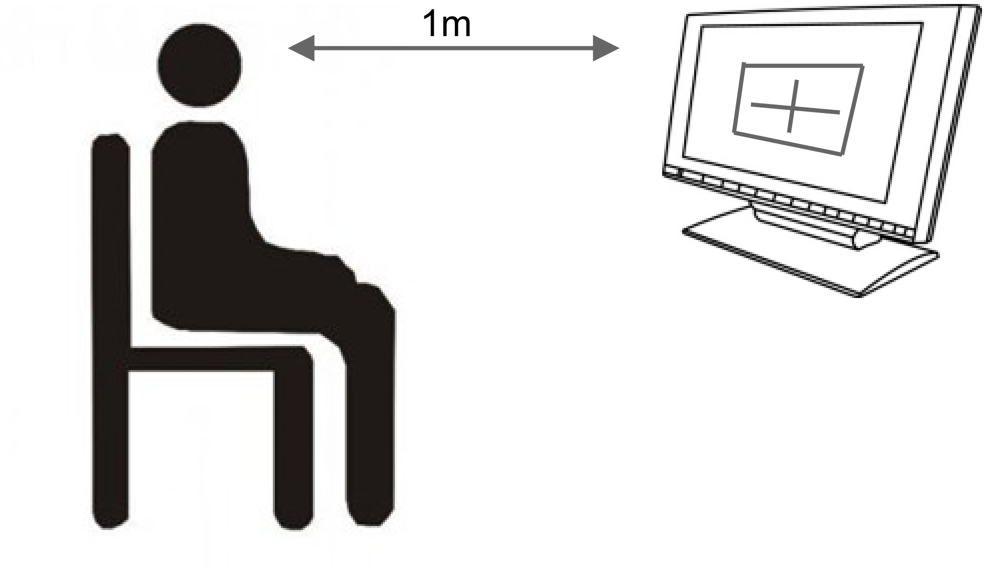
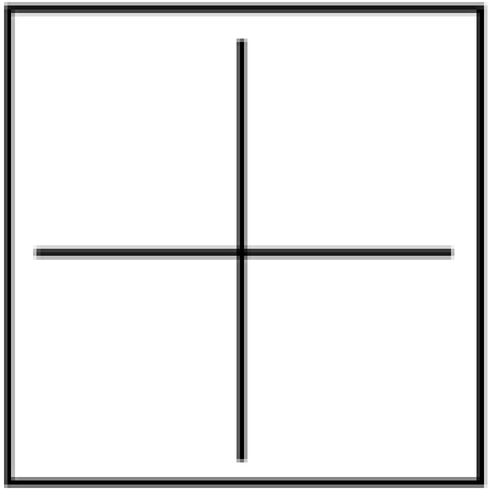


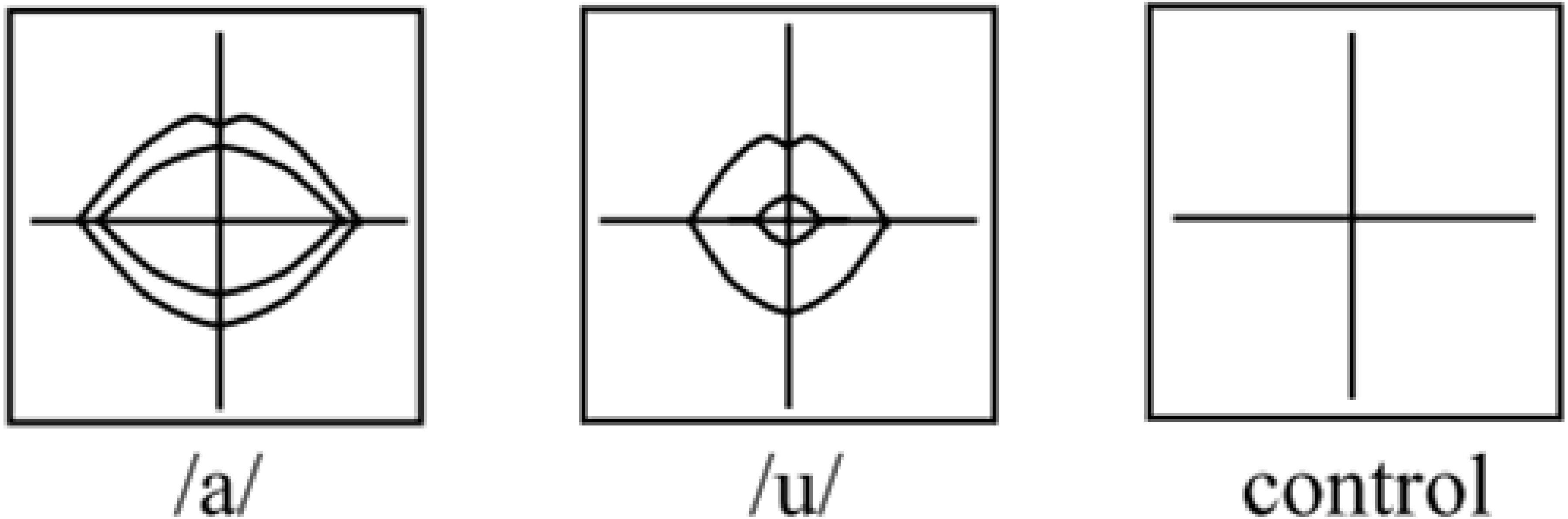
FIGURE 1.


1m

beep



fixation cross


/a/
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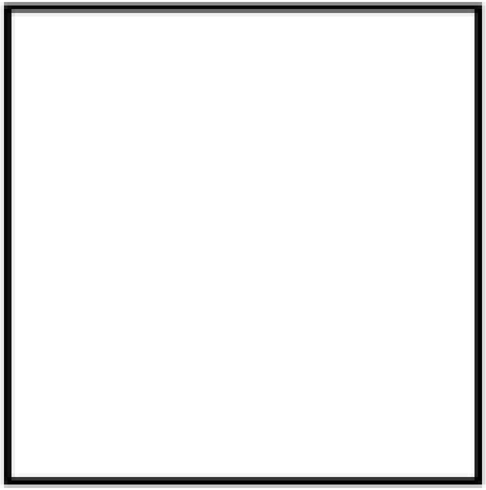
control



blank screen

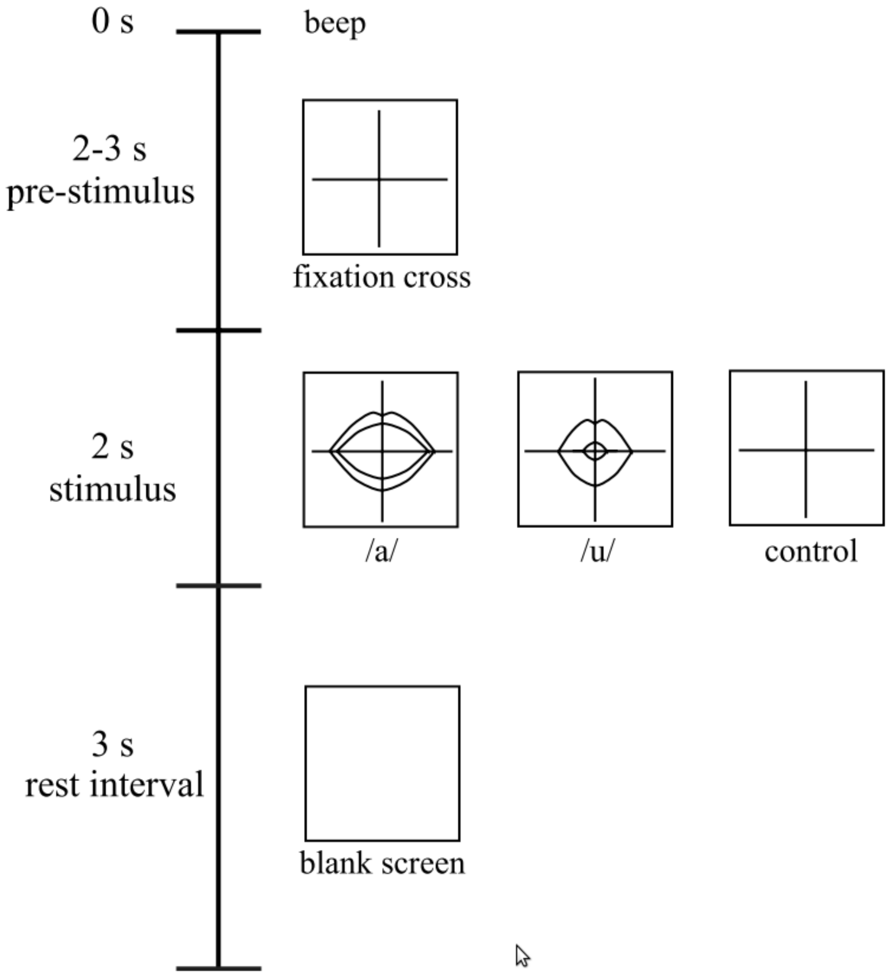


Fig. 2. Timing for one experimental trial.

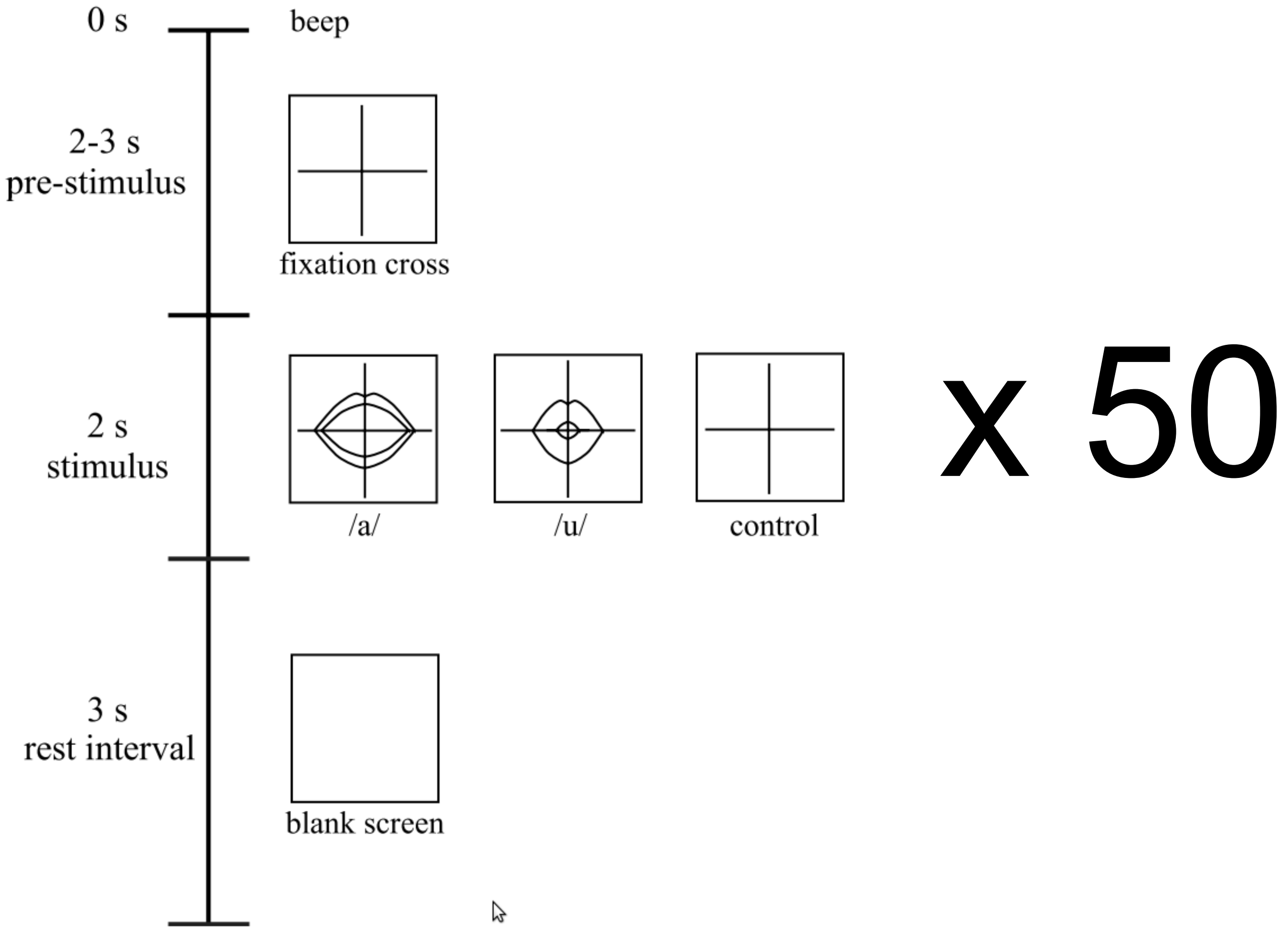


Fig. 2. Timing for one experimental trial.

Processing

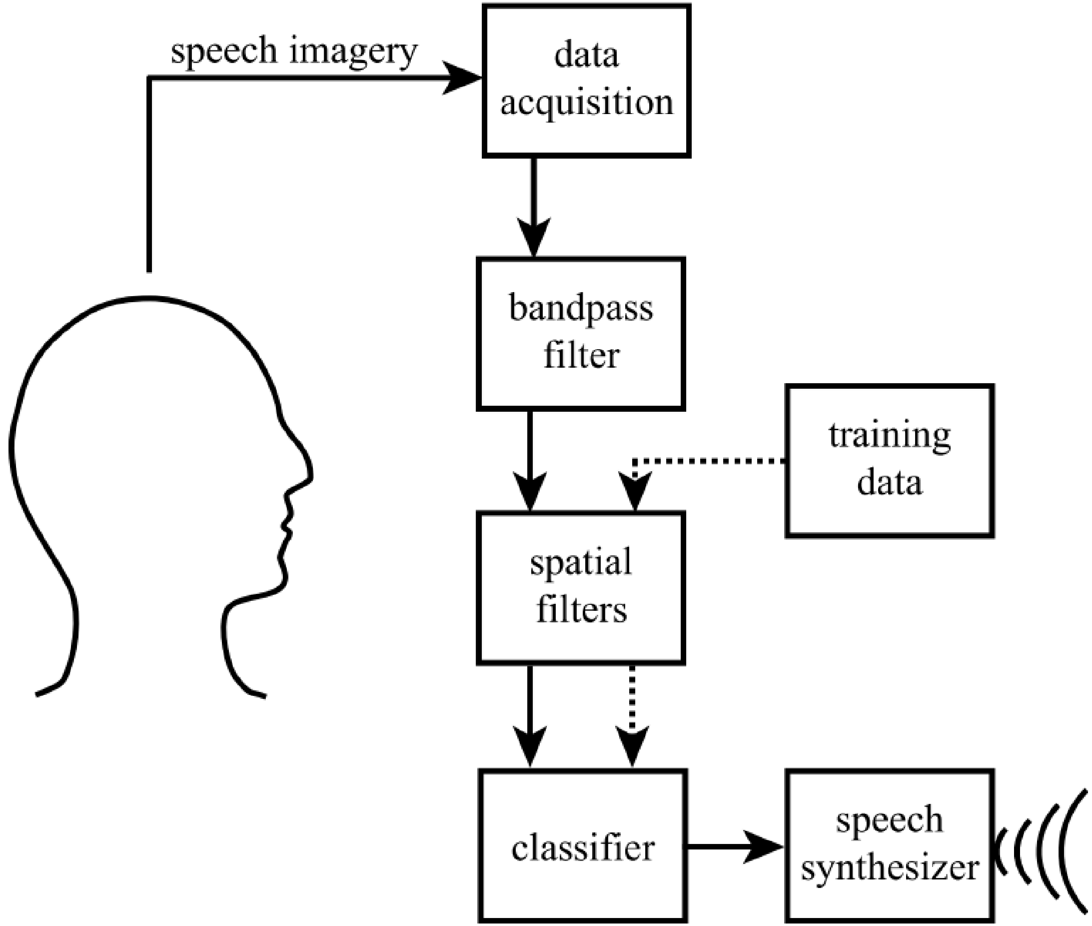


Fig. 1. Scheme for a speech prosthesis using speech imagery.

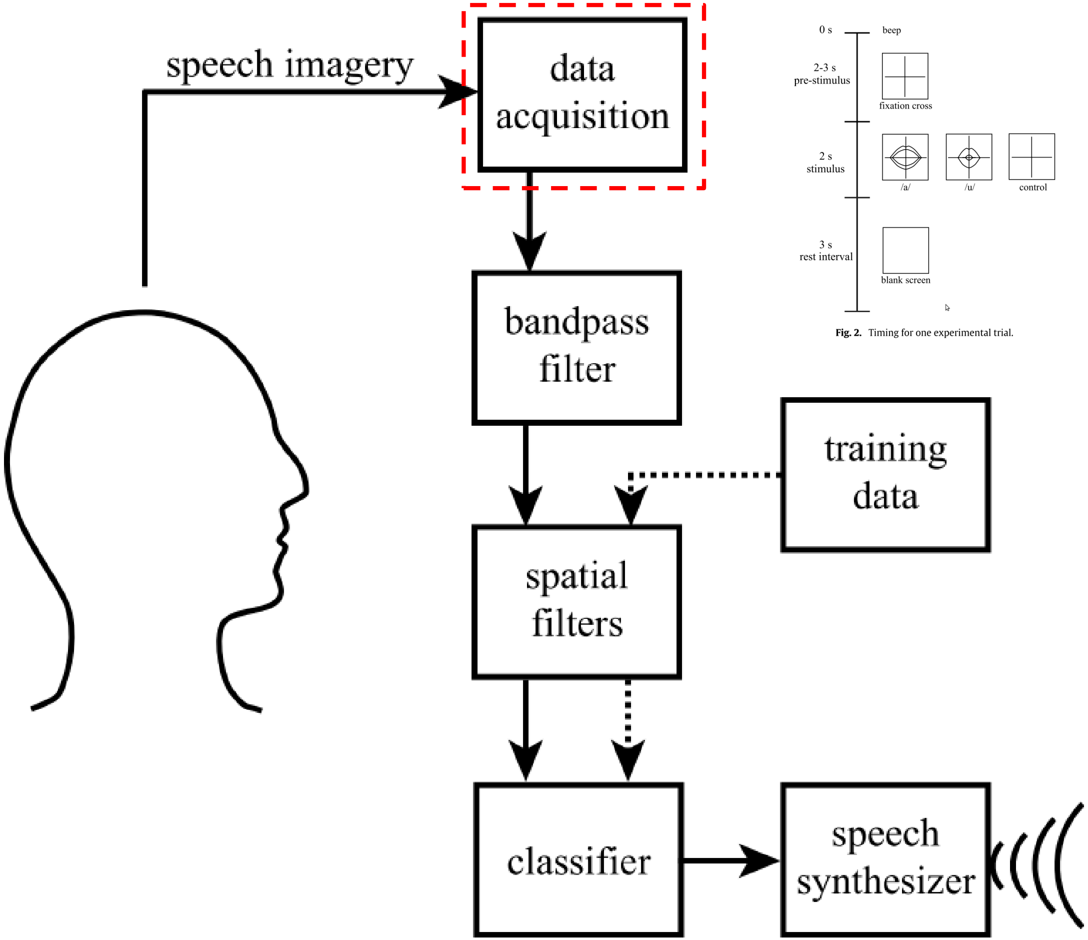
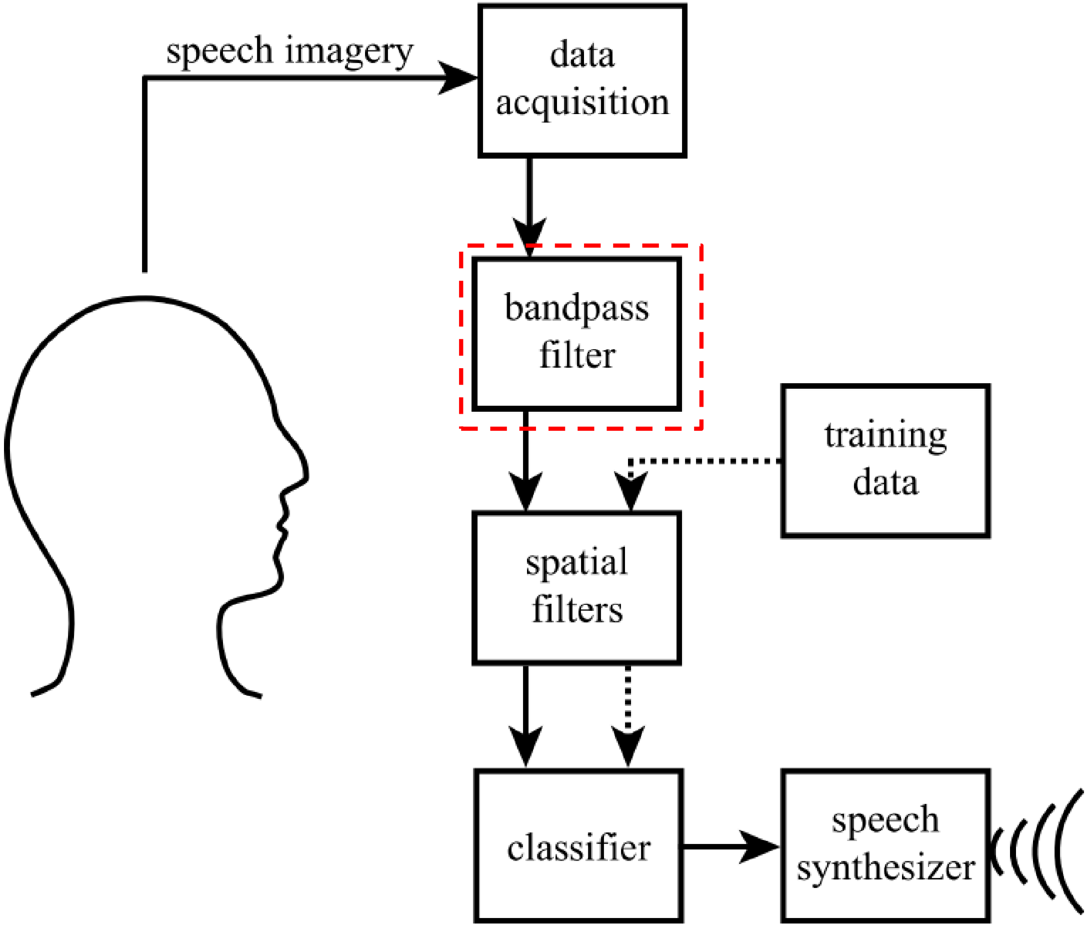


Fig. 2. Timing for one experimental trial.

Fig. 1. Scheme for a speech prosthesis using speech imagery.



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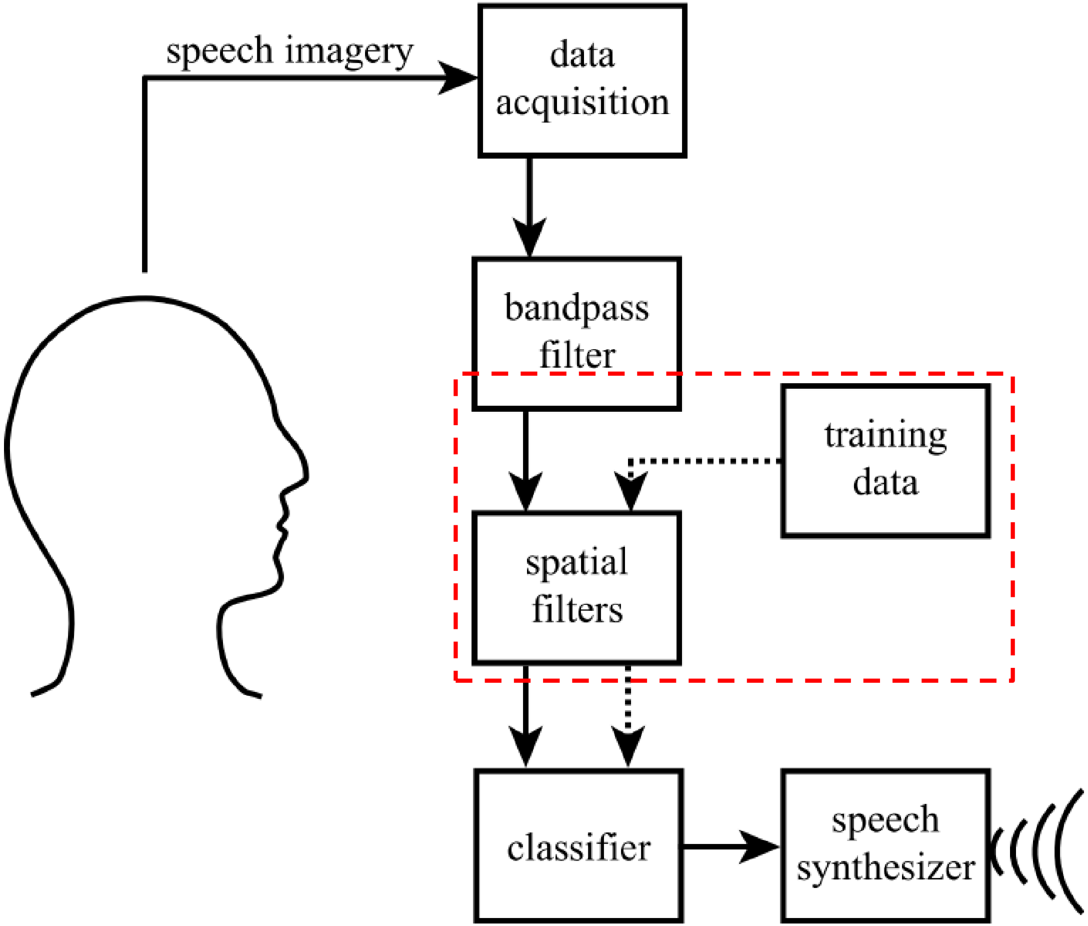


Fig. 1. Scheme for a speech prosthesis using speech imagery.

Common Spatial Patterns Method

$$\bar{C}_g = \frac{1}{n} \sum_{i=1}^{n} \frac{E_g^i (E_g^i)^{\mathrm{T}}}{trace(E_g^i (E_g^i)^{\mathrm{T}})}$$

- (1999)Designing optimal spatial filters for single-trial EEG classification in a movement task

Common Spatial Patterns Method

$$C_c = \bar{C_1} + \bar{C_2} \tag{2}$$

$$C_c = V_c \lambda_c V_c^{\mathrm{T}}, \tag{3}$$

Vc is a matrix of eigenvectors
λc is a diagonal matrix of eigenvalues

Common Spatial Patterns Method

$$W = \sqrt{\lambda_c^{-1}} V_c^{\mathrm{T}} \tag{4}$$

- Whitening transformation
- Equalizes the variances in eigenspace

Common Spatial Patterns Method

$$S_g = W\bar{C_g}W^{\mathrm{T}} \tag{5}$$

$$S_1 = U\lambda_1 U^{\mathrm{T}} \quad \text{and} \quad S_2 = U\lambda_2 U^{\mathrm{T}}, \tag{6}$$

$$Z_g^i = PE_g^i. \tag{7}$$

Optimized for discriminating the two groups

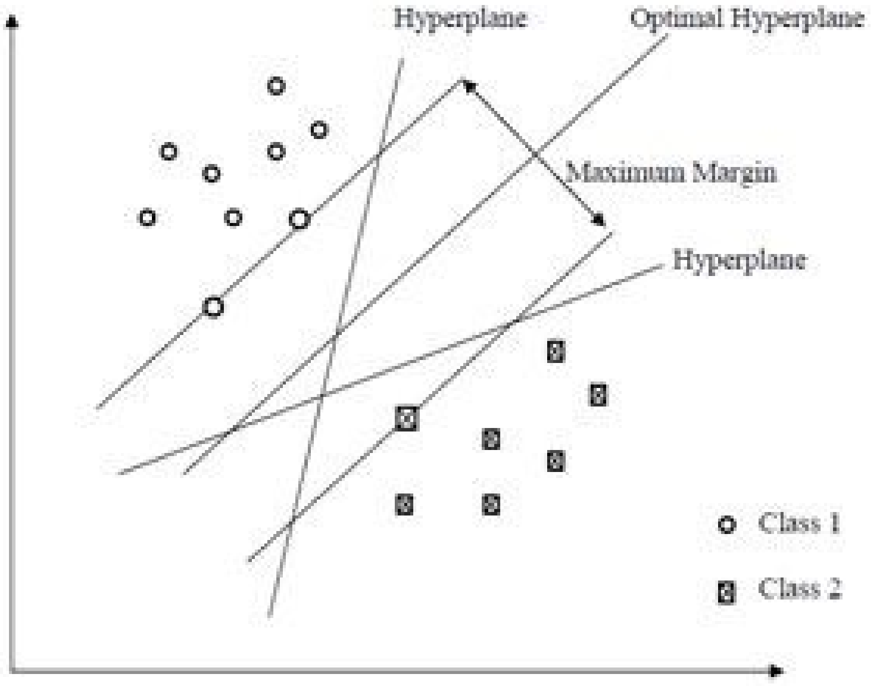
Classification

- 30 randomly selected epochs
- 20 epoch testing set
- Procedure repeated 20 times
    - (20X cross validation)

Support Vector Machine Classifier

- Strong generalization performance
- Acceptable training time
- Logistically simple to implement
- LIBSVM: A library for support vector machines
  - Chang, C.,&Lin, C. (2008)

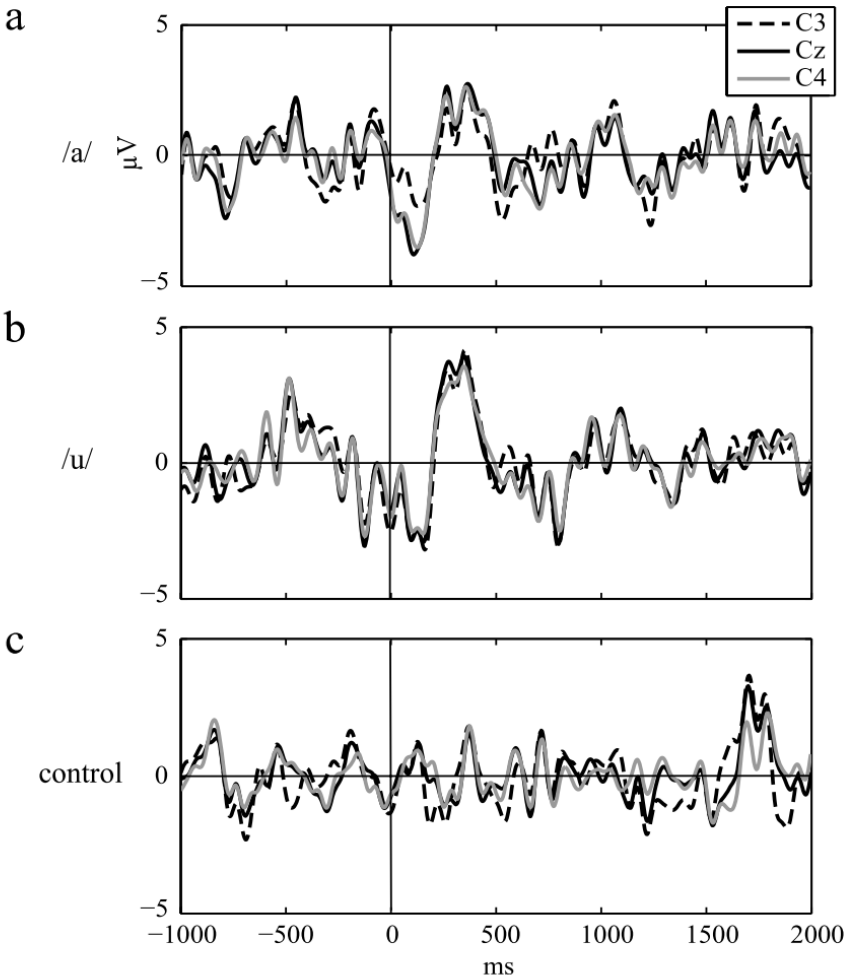
Support Vector Machine Classifier



Support Vector Machine Classifier

$$K(x, x') = e^{-\gamma \|x - x'\|^2},$$

Results



a
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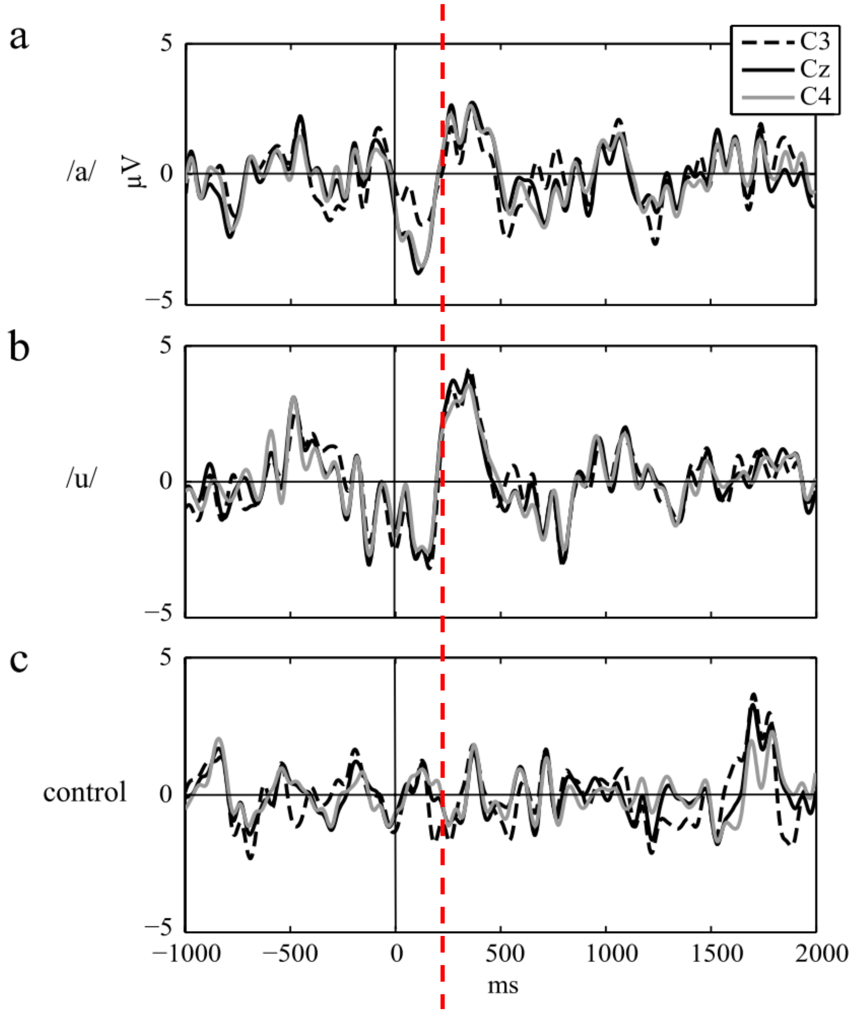
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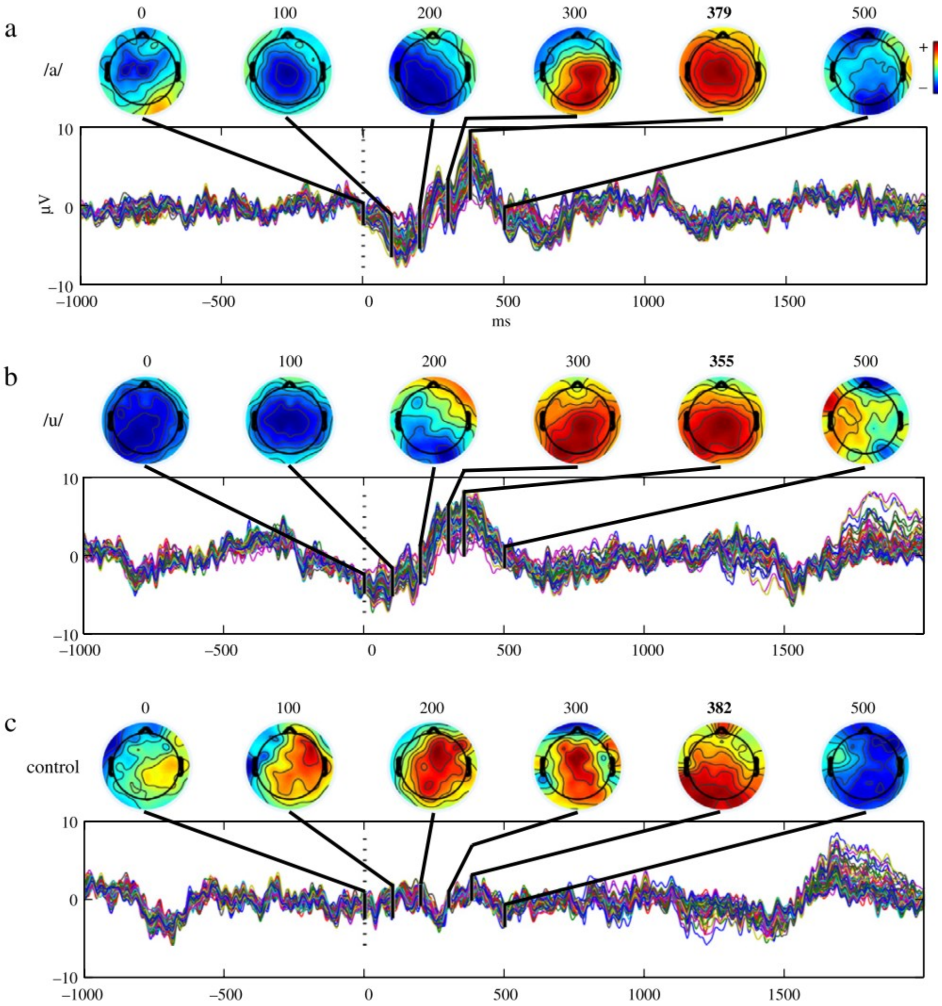
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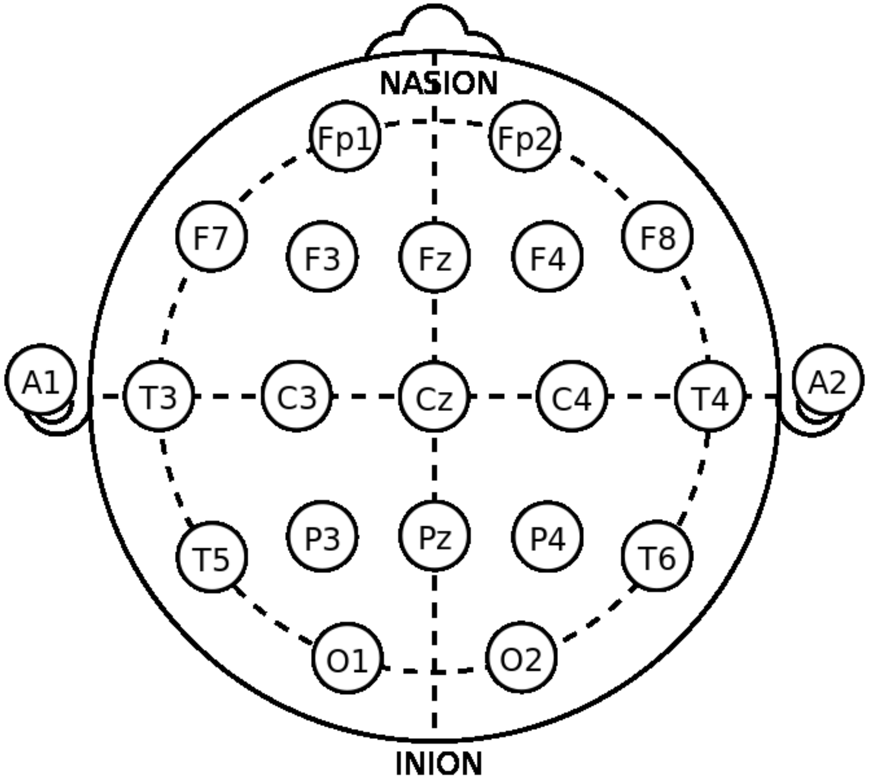
Scalp Map


NASION
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F4
F8
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T3
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T5
P3
Pz
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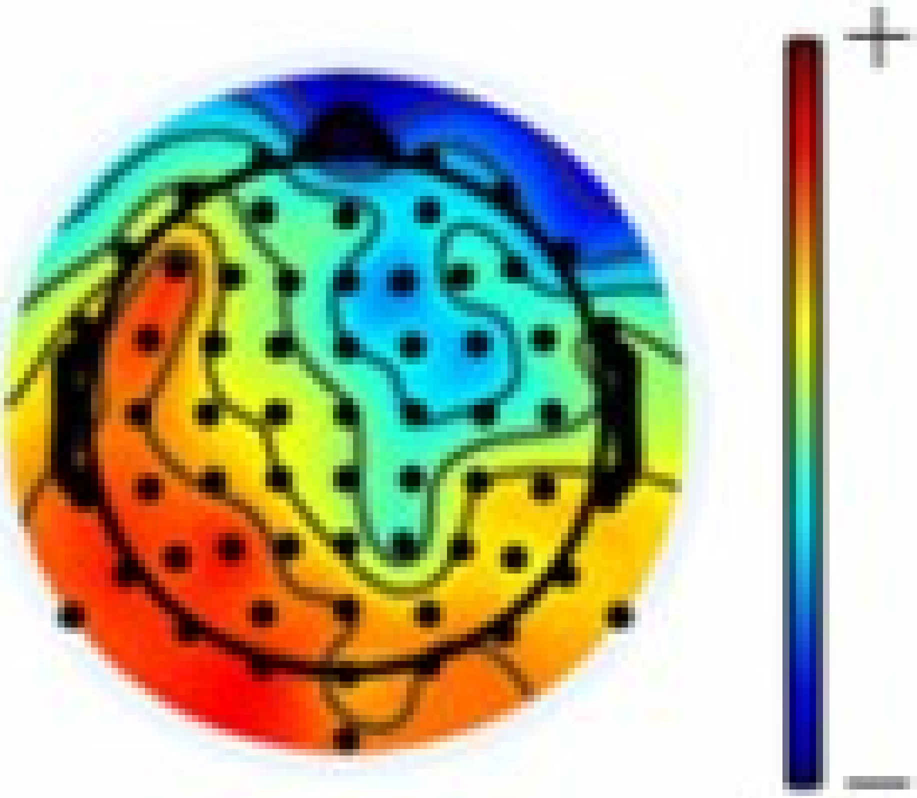
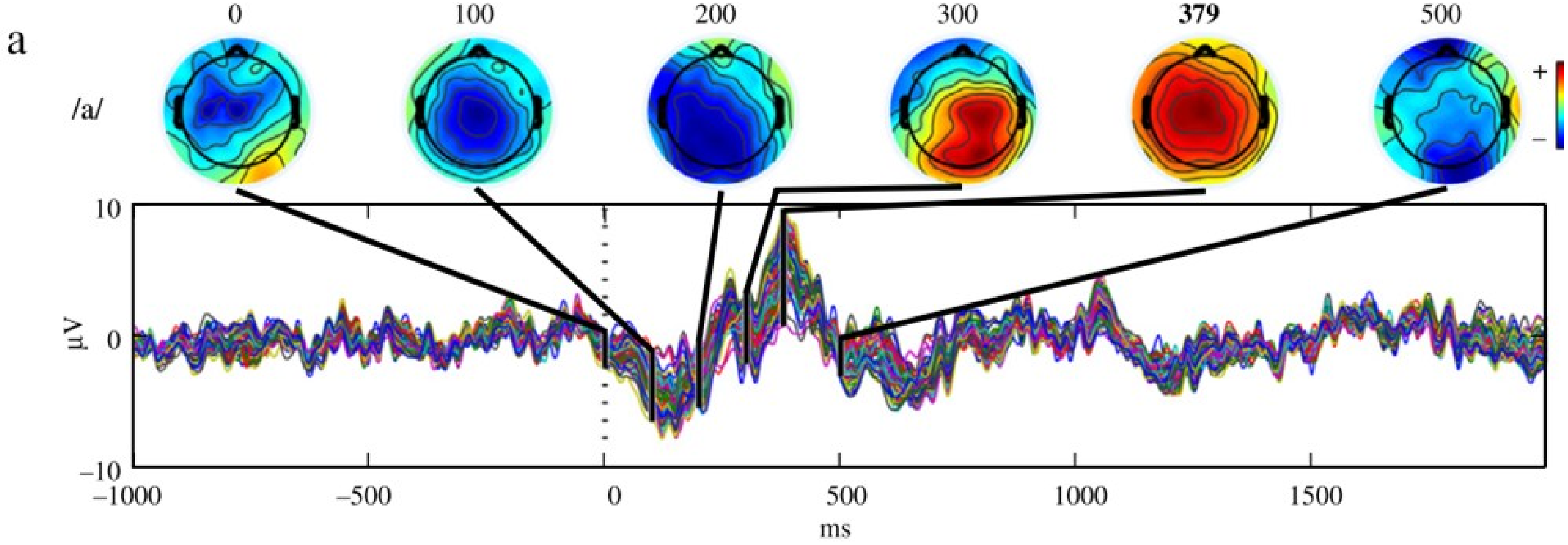
T6
O1
O2
INION

Scalp Map





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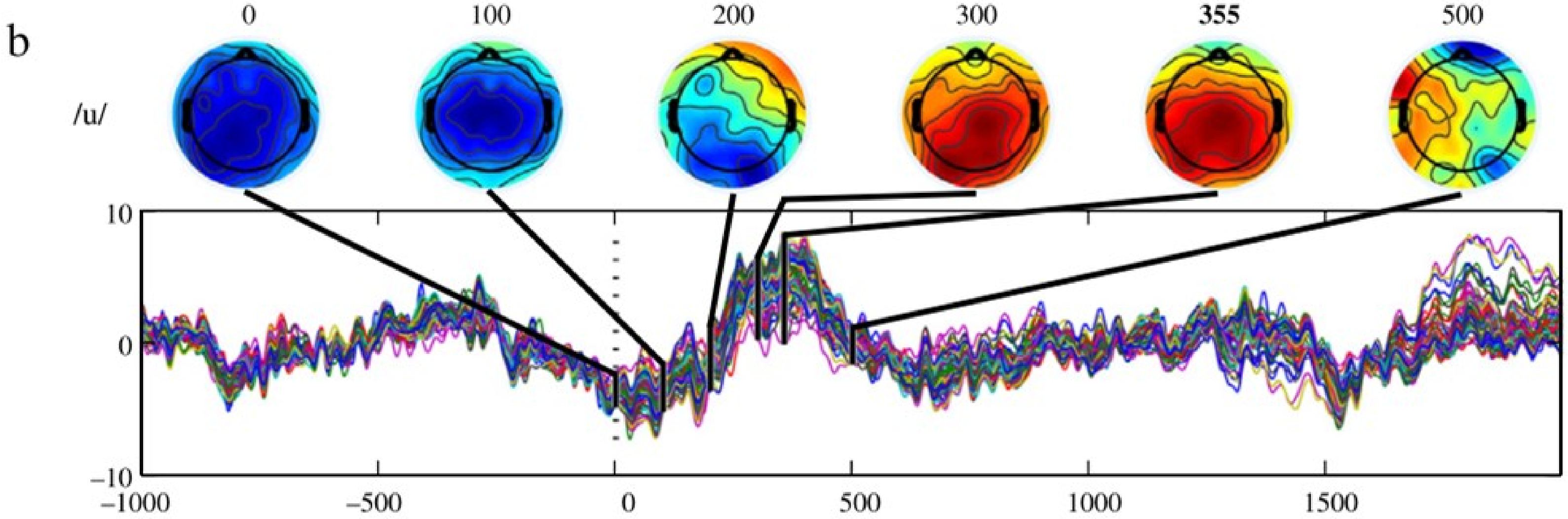
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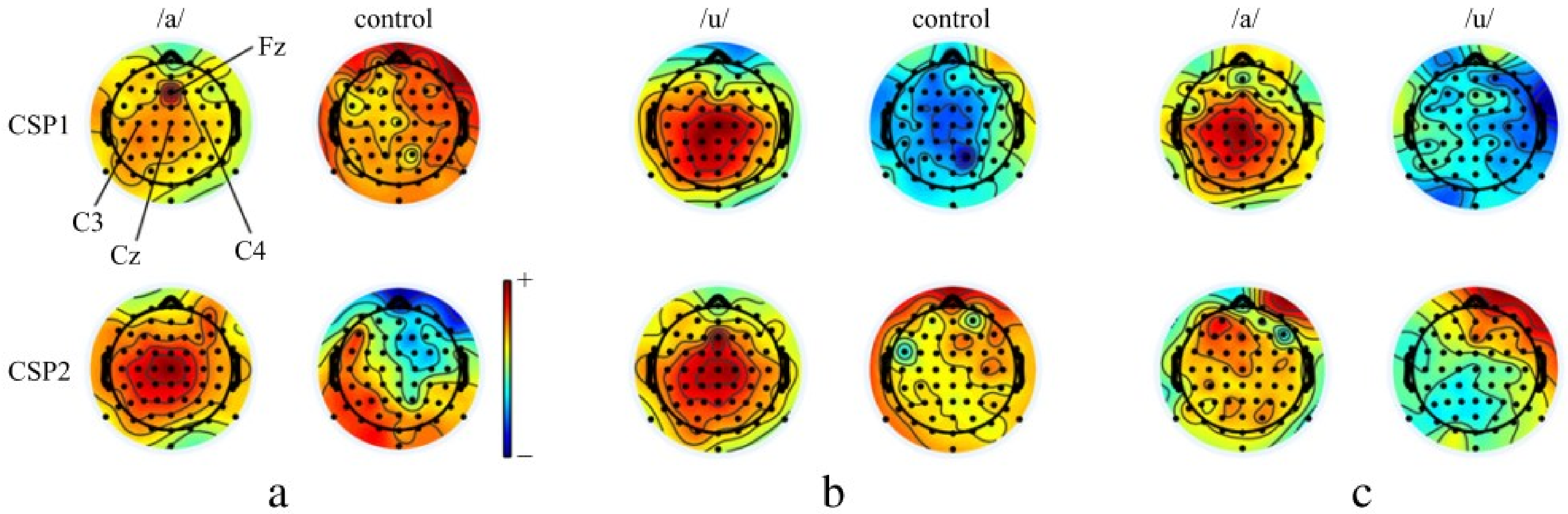


/a/
control
/u/
control
/a/
/u/
Fz
CSP1
CSP2
C3
Cz
C4
+
–
a
b
c

	/a/:cont.	/u/:cont.	/a/:/u/	Overall
S1	79 ± 3	82 ± 4	72 ± 3	78 ± 5
S2	71 ± 5	72 ± 4	60 ± 5	68 ± 7
S3	67 ± 4	80 ± 3	56 ± 4	68 ± 12

Significance threshold = 59% ($\alpha = 0.05$).

Experiment Dataset

http://www.brainliner.jp/data/brainliner-admin/Speech_Imagery_Dataset

Questions?

Imagined Speech Classification with EEG Signals for Silent Communication: A Preliminary Investigation into Synthetic Telepathy

K. Brigham, B.V.K.V. Kumar (2010)

Presented by Peter Hamilton

Brain-Compute… faces (BCI)

Related Work

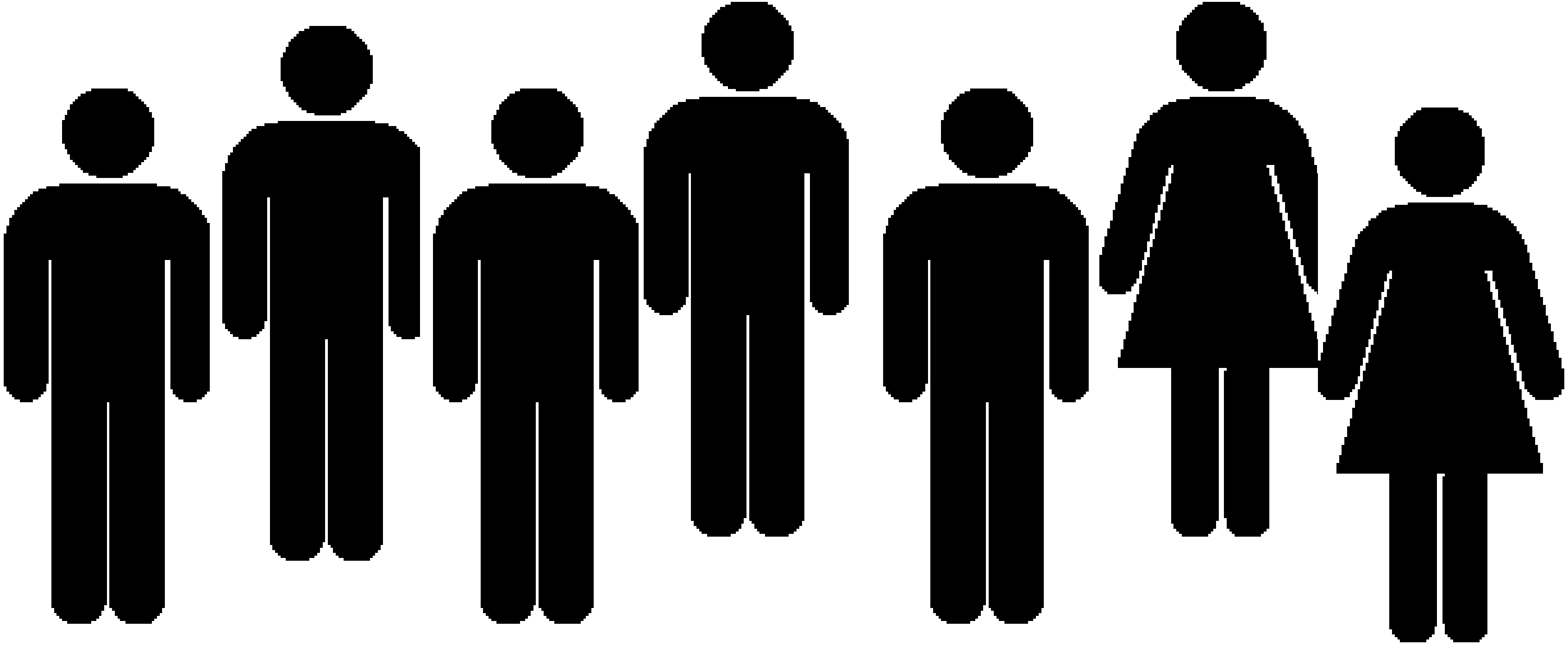
C. S. DaSalla, H. Kambara, M. Sato, Y. Koike. "Single-trial classification of vowel speech imagery using common spatial patterns."(2009)

- Sounds familiar

M. D'Zmura, S. Deng, T. Lappas, S. Thorpe, R. Srinivasan. "Toward EEG sensing of imagined speech"(2009)

- /ba/ or /ku/ vs /a/ or /u/

Data Collection

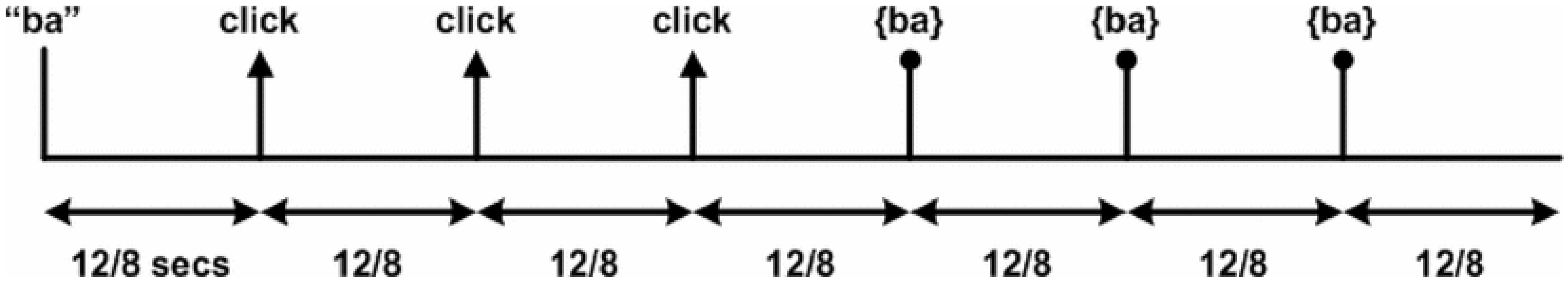


6 Sessions x 20 Trials x 2 Syllables = 120 trials / Subject

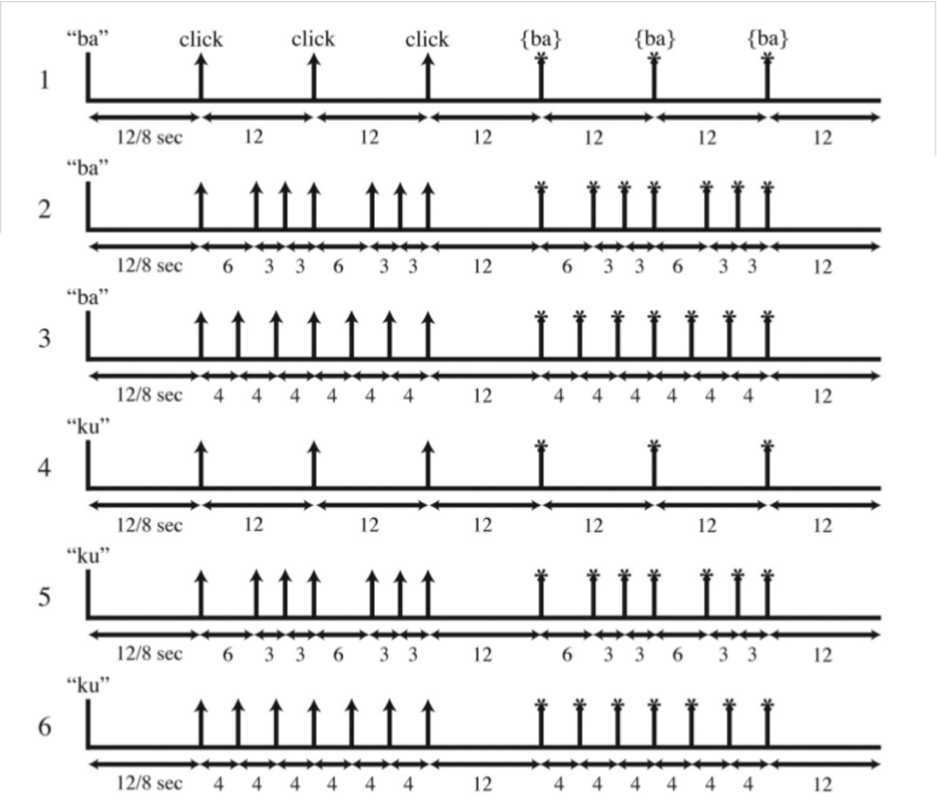
Equipment

- 128 Channel Sensor Net
- 1024Hz Sample Rate
- Made by Electrical Geodesics

Trial



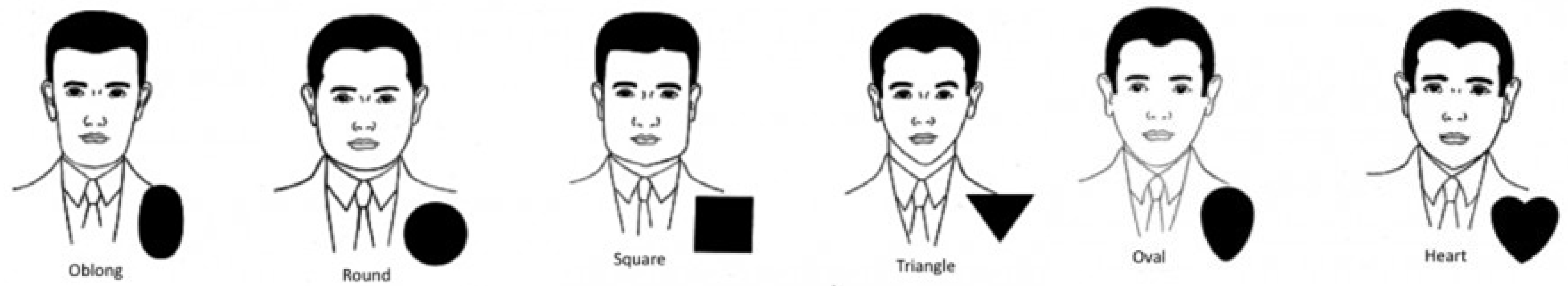
Example Trial Timeline



Data Preprocessing

Classification Challenges

- Eye Blinks and Electromyographic Activity
- Low signal-to-noise ratio
- No Two Heads are the Same



Modeling EEG Signals

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t), \quad (1)$$

x(t) is a vector of observed noisy sensor signals from N sensors
A is the forward model relating the source activity to the sensor activity
s(t) is a vector of M unknown sources with M ≤ N
n(t) represents background activity that would be considered noise

Independent Component Analysis

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t), \qquad (1)$$

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t), \qquad (2)$$

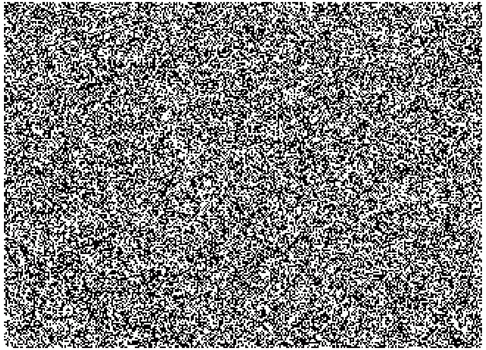
$$\mathbf{W}_{t+1} = (\mathbf{I} + \mu(\mathbf{C}_{y,y}^{1,3}\mathbf{S}_y^3 - \mathbf{I}))^{-1}\mathbf{W}_t \,, \qquad (3)$$

Artifact Removal

- Removed:
  - 18 electrodes closest to neck, eyes, temple
  - trials where electrodes exceed the thresholds of +/- 30μV
- Filtered:
  - range of 4 -25 Hz

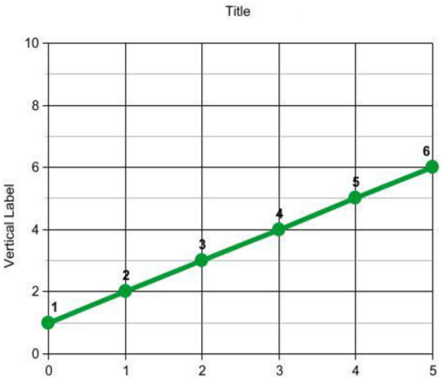
Hurst Exponent

- Vorobyov and Cichocki(2002)
- Measures the predictability of a time series (0 - 1)



0

1



Extracting Useful Sources

- Hurst Exponent
  - 0.58 – 0.69 : heartbeat and eye blink artifacts
  - 0.70 – 0.76 : biological phenomena (“interesting”)

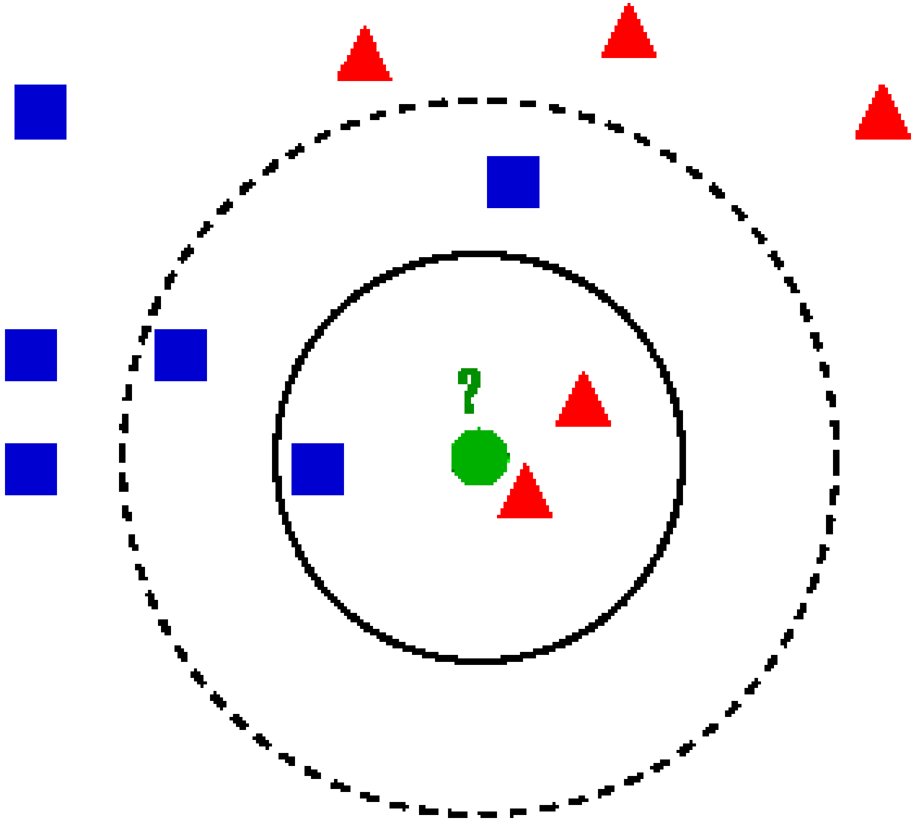
Feature Extraction and Imagined Syllable Classification

Univariate Autoregressive (AR) Model

$$x[n] = -\sum_{k=1}^{p} a_k x[n-k] + e[n], \qquad (4)$$

x[n] is the observed signal at time n,
ak are the coefficients of an AR model of order p
e[n] is white noise

k-Nearest Neighbors



Imagined Syllable Classification

- 3-Nearest Neighbors classifier
- Euclidean distance between AR model coefficients
- 100 iterations of 2- or 4-fold cross validation

Results

Trial Refinement

- Not all of the trials may contain usable information
- Hurst exponent threshold (< 0.67)
- Only trials that contained more than 90% of "useful" electrodes were retained

TABLE I. AVERAGE CLASSIFICATION ACCURACY FOR EACH OF THE 7 SUBJECTS. ALSO LISTED IS THE BREAKDOWN OF TRIALS PER CLASS (/BA/ OR /KU/) AND THE TOTAL NUMBER OF TRIALS FOR EACH SUBJECT.

	Classification Rate	# of /ba/ Trials	# of /ku/ Trials	Total # of Trials
S1	0.56	4	11	15 trials
S2	0.88	4	7	11 trials
S3	--	1	1	2 trials
S4	0.46	7	6	13 trials
S5	0.75	14	10	24 trials
S6	0.81	4	8	12 trials
S7	0.67	6	2	8 trials

TABLE II. AVERAGE CLASSIFICATION ACCURACY FOR DIFFERENT COMBINATIONS OF SUBJECT DATA.

	Classification Rate	**# of Trials**
All Subjects	0.61	85 trials
S2, S5, S6, and S7	0.72	62 trials

Conclusion

Brain Computer Interfaces are hard

Questions?