A High-Speed Brain-Computer Interface Based on Steady-State Visual Evoked Potentials

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Outline

1. **Introduction**
   - Brain-computer interface (BCI)
   - Steady-state visual evoked potentials
   - BCI based on SSVEPs
2. **Material and Methods**
   - Display-based stimulus presentation
   - Target identification algorithms
3. **Applications**
   - A high-speed BCI speller
   - (Assessment of visual impairment in glaucoma)
4. **Summary**

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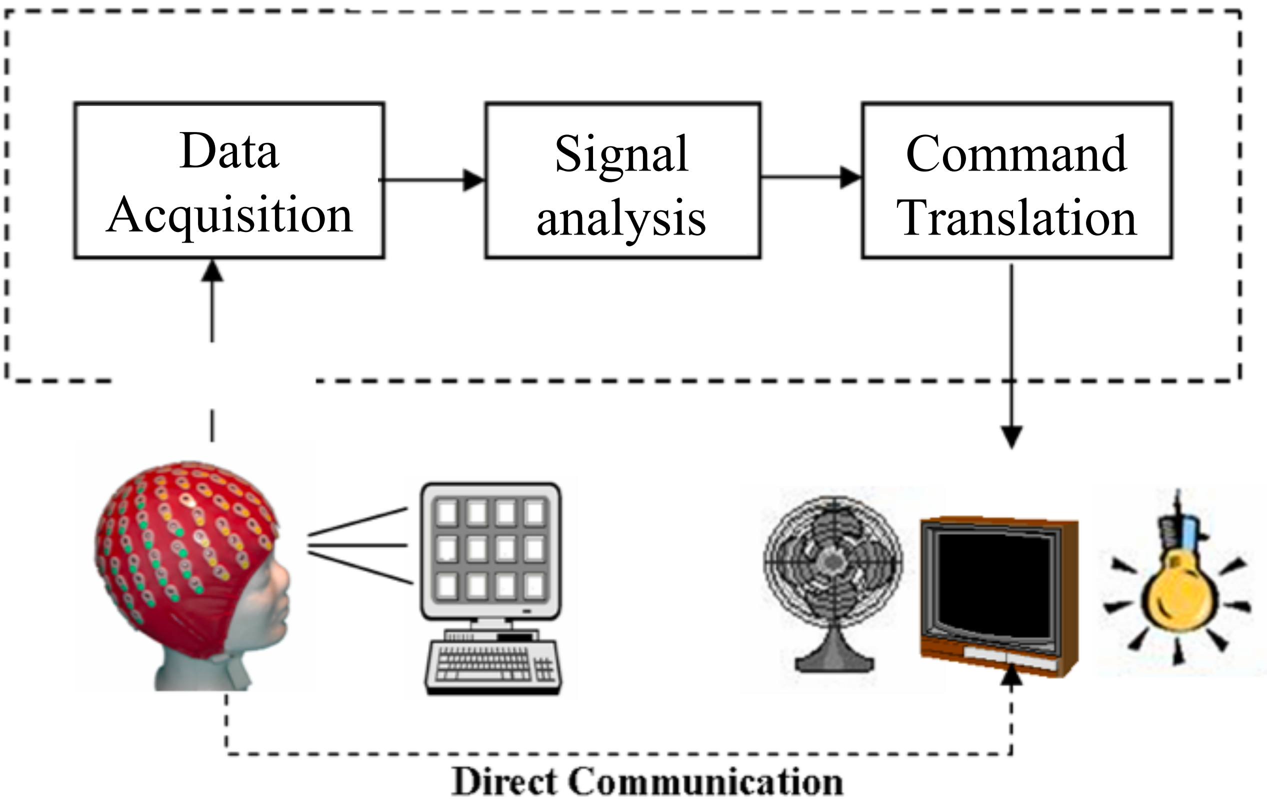
Brain-computer interface (BCI)

- BCI provides a new communication channel between external environments and human brain.



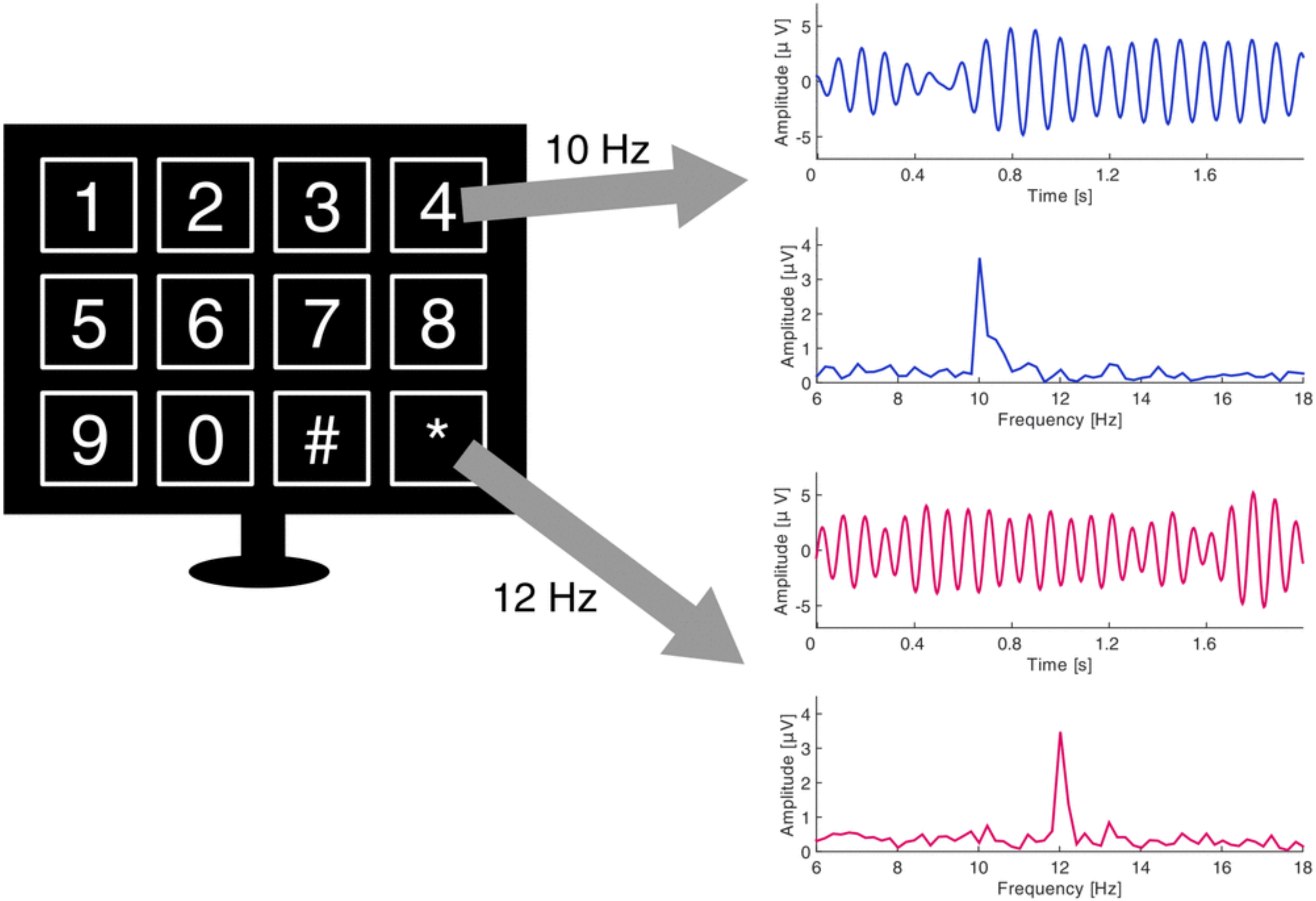
Wang et al., *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2006

Steady-State VEPs (SSVEPs)

- Steady-state visual evoked potentials (SSVEPs) are brain's responses to repetitive visual stimulation.
- An SSVEP is characterized by sinusoidal-like waveforms at stimulus frequency and its harmonics.

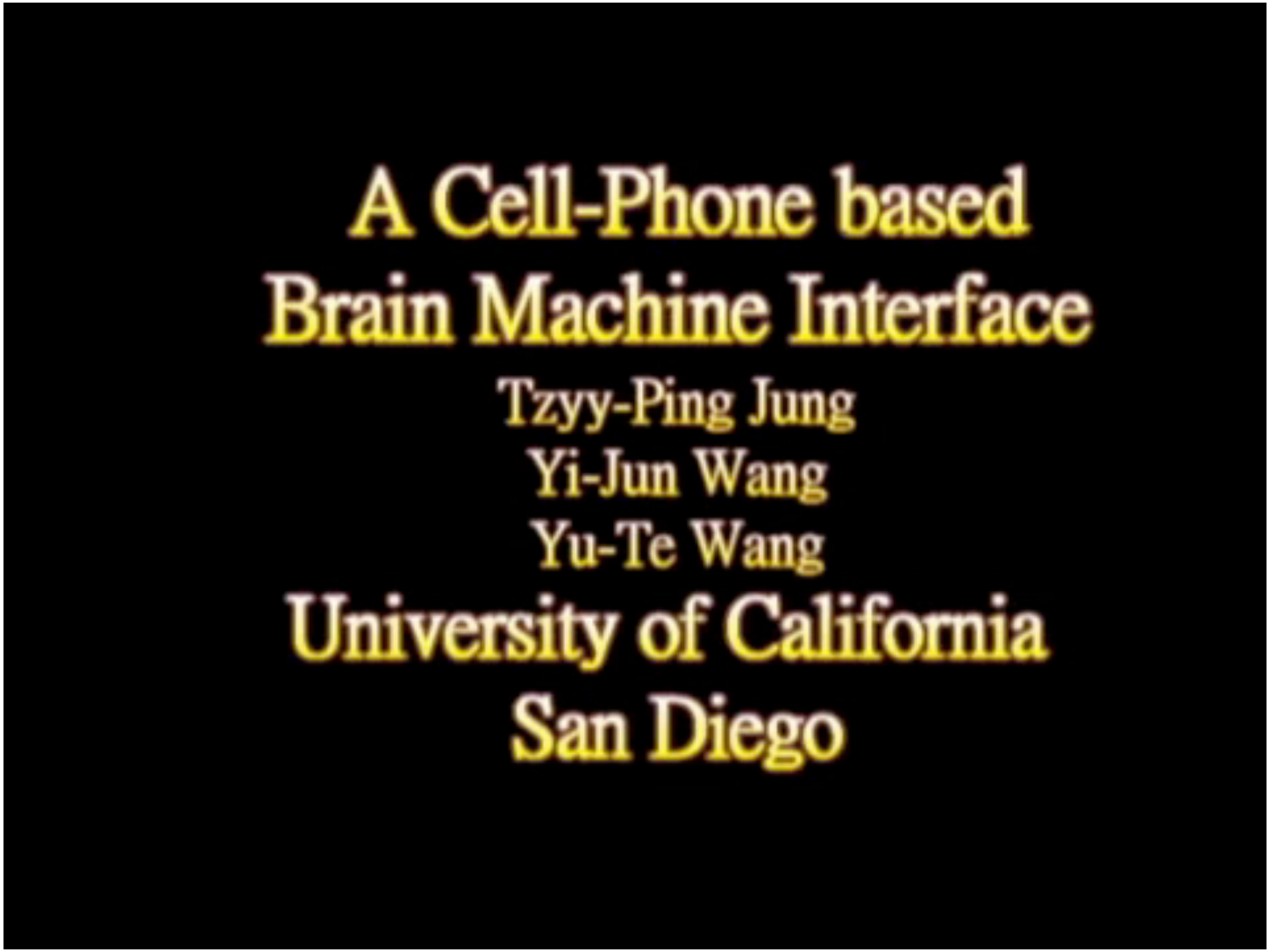
Vialatte et al., *Prog. Neurobiol*. 2010

BCIs based on SSVEPs



Wang et al., *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2006

SSVEP-based BCI



Wang et al., Electron Lett. 2010

Performance evaluation

- The performance of BCIs has been evaluated by an information transfer rate (ITR) [bits/min].

Accuracy of target identification

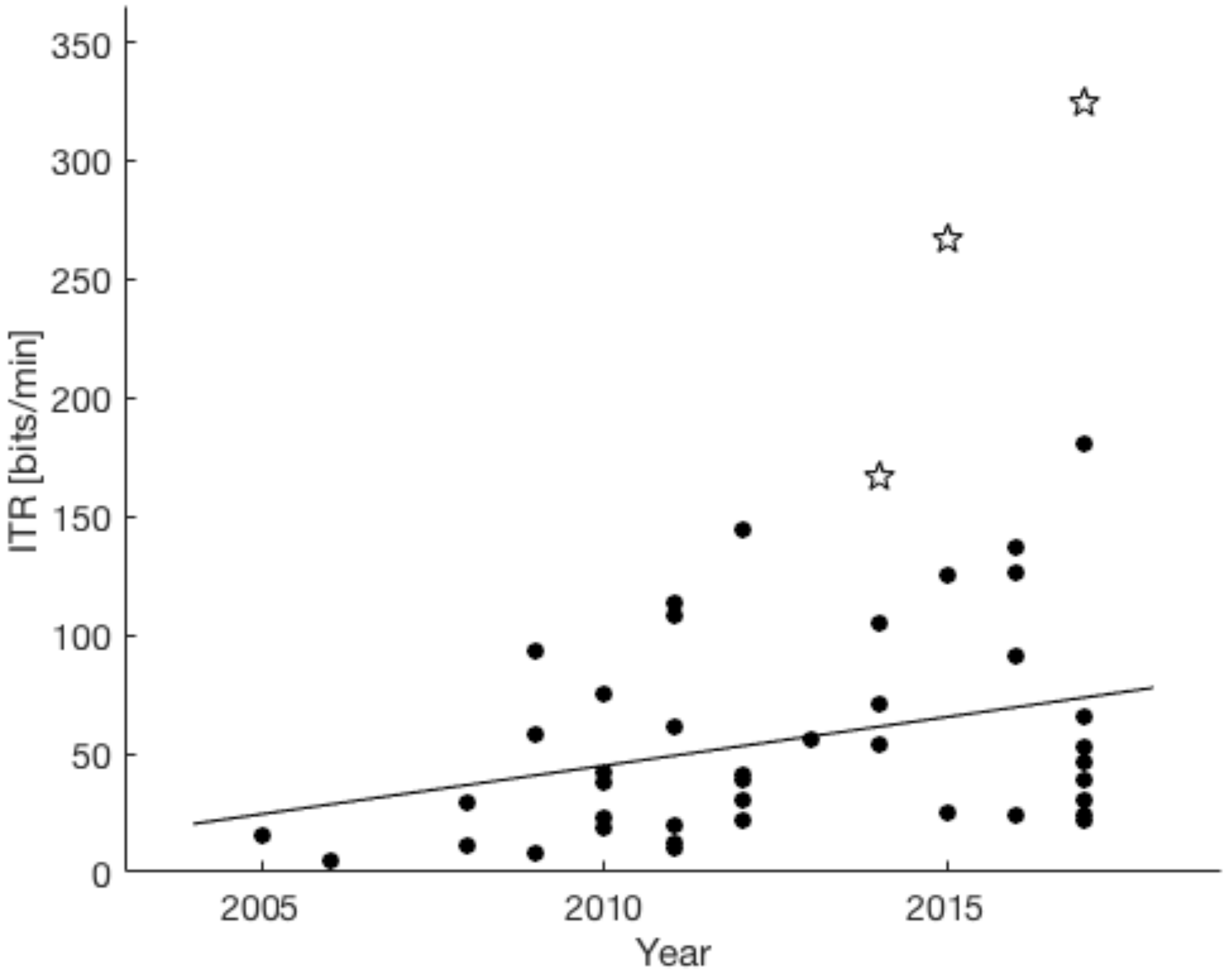
$$\mathrm{ITR} = \left(\log_2 \underline{N} + P \log_2 \underline{P} + (1-P)\log_2 \left[\frac{1-P}{N-1} \right] \right) \times \frac{60}{\underline{T}}$$

The number of targets

Average time for a selection [s]

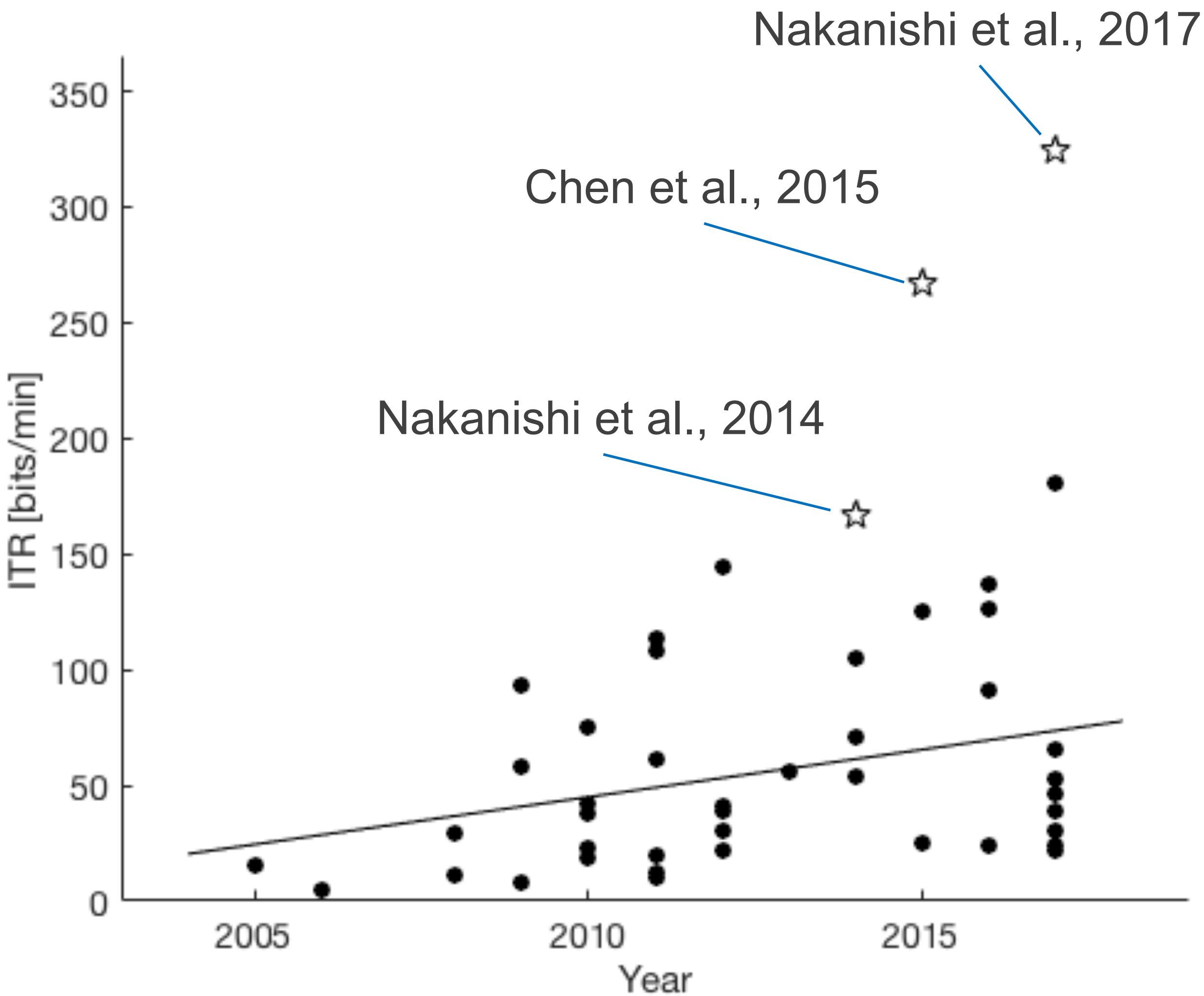
Cheng et al., *IEEE Biomed. Eng*, 2002

Performance improvement



Chen et al., *Proc. Natl. Acad. Sci. USA*, 2015

Performance improvement



Chen et al., *Proc. Natl. Acad. Sci. USA*, 2015

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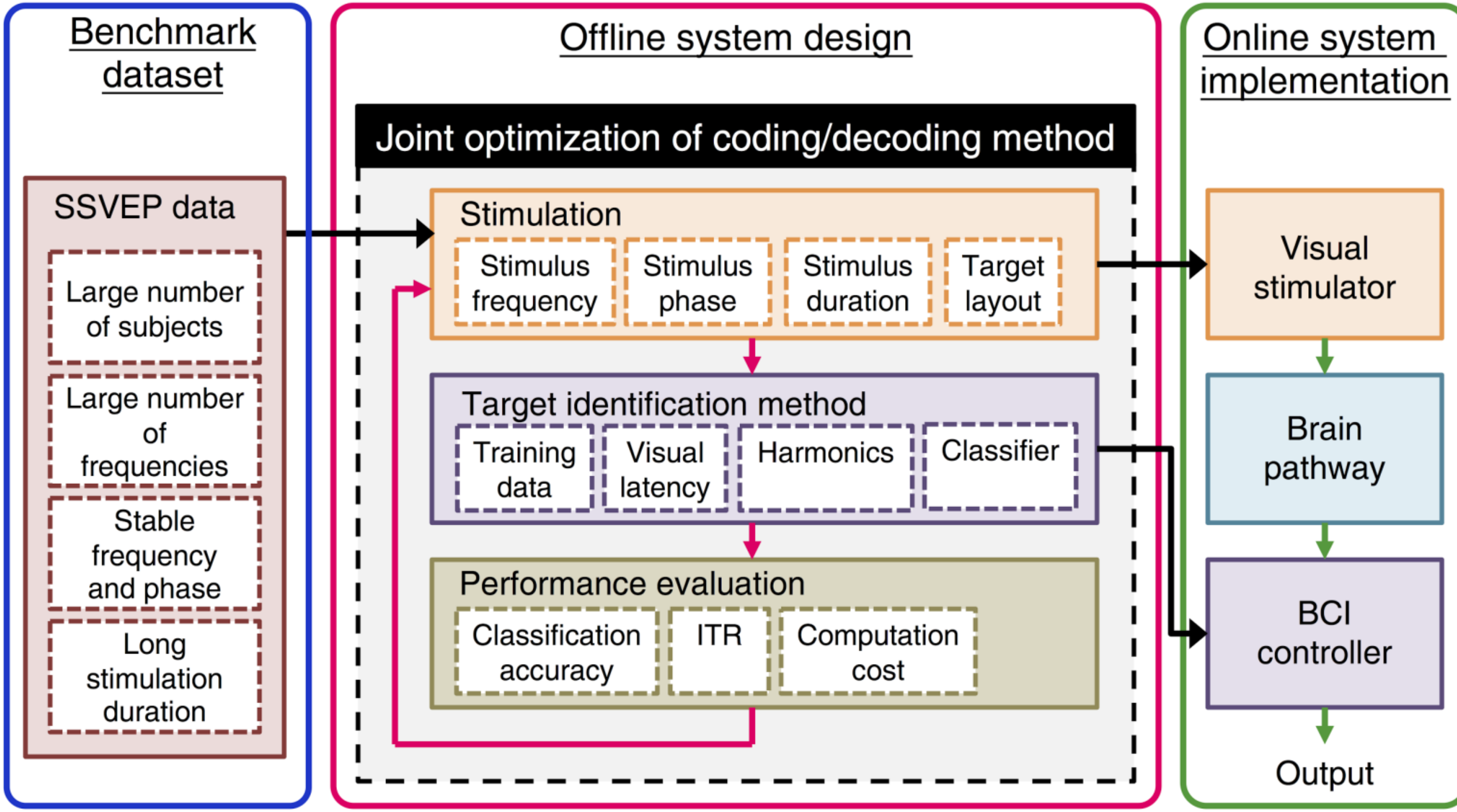
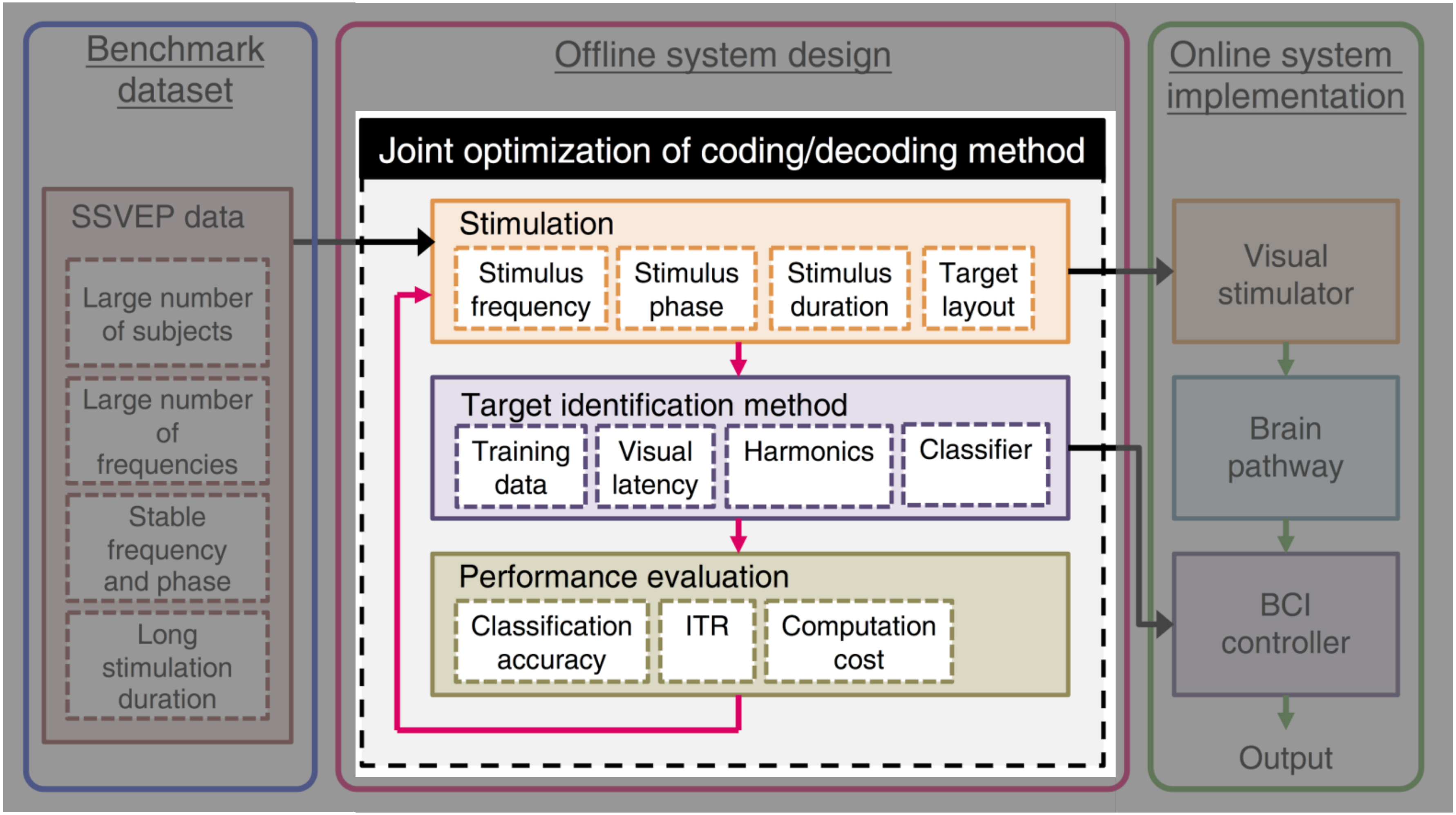
Framework of designing SSVEP BCI



Chen et al., *Proc. Natl. Acad. Sci. USA*, 2015

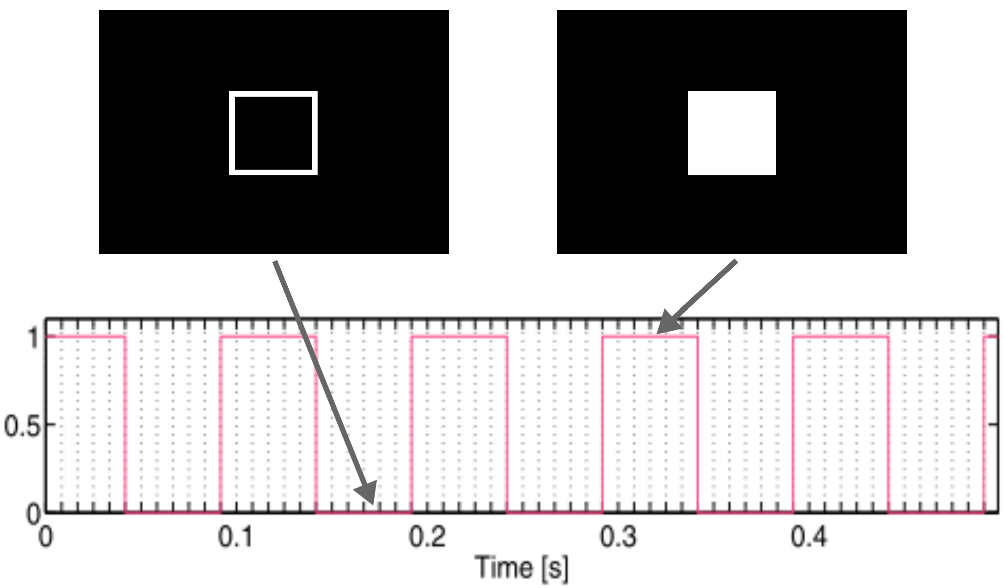
Framework of designing SSVEP BCI

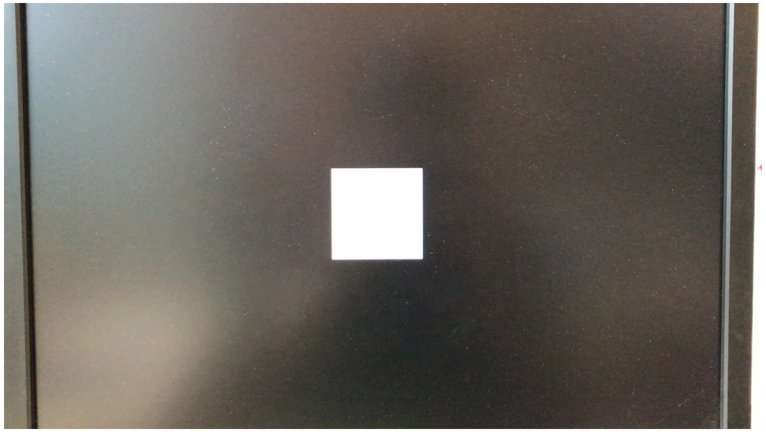


Chen et al., *Proc. Natl. Acad. Sci. USA*, 2015

Display-based stimulus presentation

- Stimulation parameters (e.g., color, size, position,…) can be flexibly configured than light-emitting diodes (LED)-based method.
- Stimulus frequency can be produced by reversing the stimulus pattern between white and black (e.g., ‘000111000111…’).





Wu et al., *Med. Eng. Physics,* 2008

Challenge in display-based stimulation

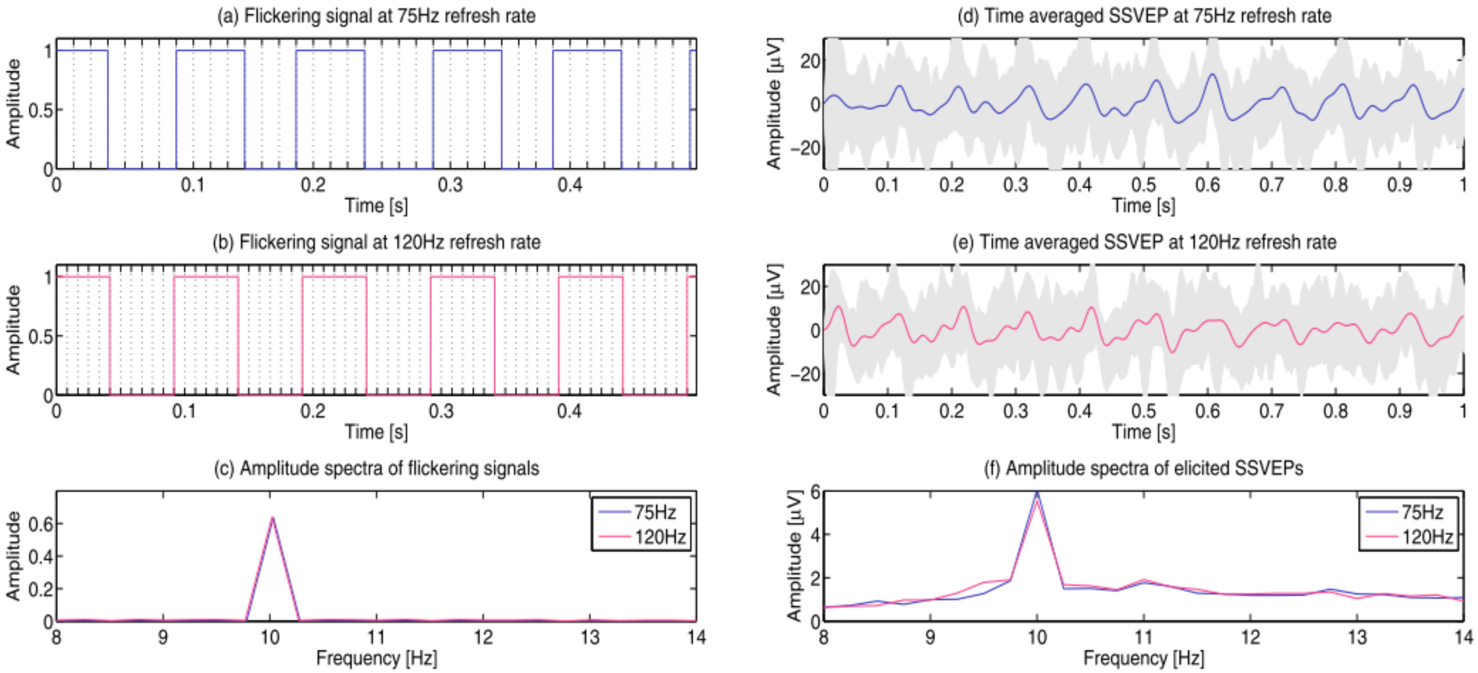
- The number of frequencies that can be presented on a monitor is limited by its refresh rate.
- It is impossible to realize the frequencies by which the refresh rate can not be divided.
- For example, if the refresh rate is 60 Hz, …

  1. 10 Hz can be realized with 6 frames/cycle (i.e., '111000111000').
  2. 11 Hz cannot be realized because the black/white reversals should occur every 2.73 frames/cycle.

Wang et al., *Electron. Lett*. 2010; Nakanishi et al., *PLoS One,* 2014

Generating flexible frequencies

- Our new approach can realize flexible frequencies by approximating frequencies with a variable number of frames.



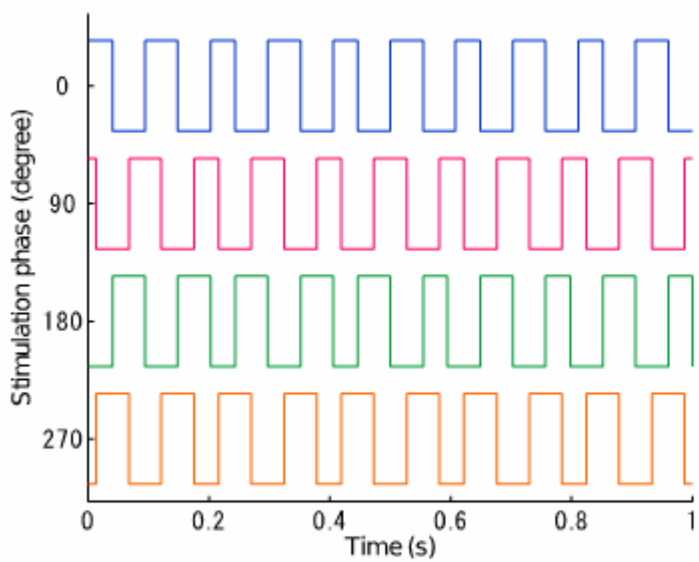
$$c(f, i) = \text{square}\left[2\pi f\left(\frac{i}{\text{RefreshRate}}\right)\right]$$

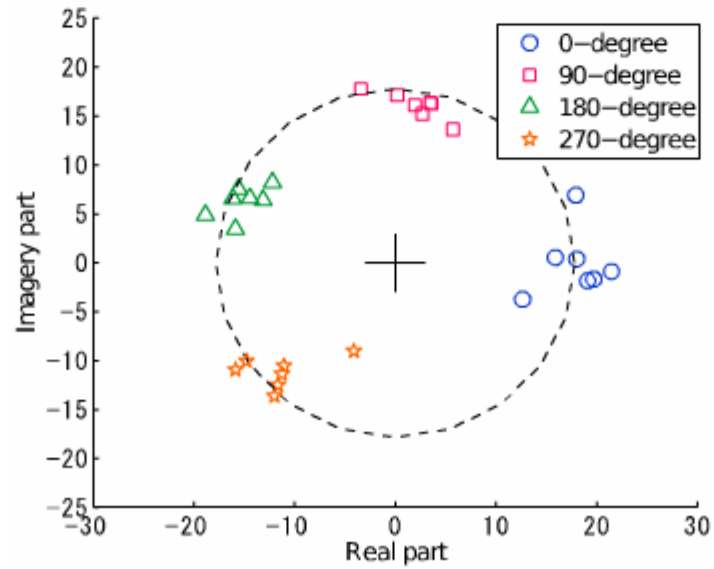
f : Stimulus frequency
i : Sampling point

Wang et al., *Electron. Lett*. 2010; Nakanishi et al., *PLoS One,* 2014

Integrating phase information

- Initial phase can also be adjusted in the stimulus waveforms using the approximation approach.





$$c(f, \phi, i) = \text{square}\left[2\pi f\left(\frac{i}{\text{RefreshRate}}\right) + \phi\right]$$

f : Stimulus frequency
Φ : Initial phase
i : sampling point

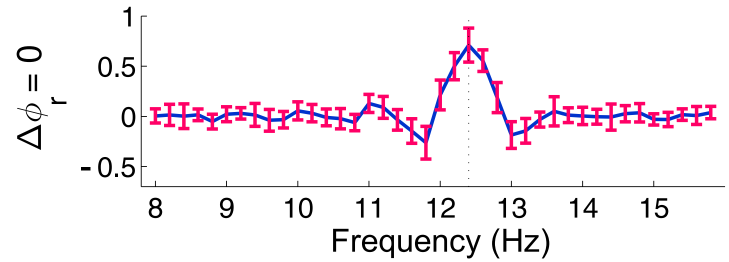
Nakanishi et al., *Int. J. Neural Syst.*, 2014

Joint frequency-phase modulation

>>HIGH SPEED BCI

8.0	9.0	10.0	11.0	12.0	13.0	14.0	15.0
8.2	9.2	10.2	11.2	12.2	13.2	14.2	15.2
8.4	9.4	10.4	11.4	12.4	13.4	14.4	15.4
8.6	9.6	10.6	11.6	12.6	13.6	14.6	15.6
8.8	9.8	10.8	11.8	12.8	13.8	14.8	15.8

Freq. (Hz)



Chen et al., *Proc. Natl. Acad. Sci. USA*, 2015

Joint frequency-phase modulation

>> HIGH SPEED BCI

8.0	9.0	10.0	11.0	12.0	13.0	14.0	15.0
8.2	9.2	10.2	11.2	12.2	13.2	14.2	15.2
8.4	9.4	10.4	11.4	12.4	13.4	14.4	15.4
8.6	9.6	10.6	11.6	12.6	13.6	14.6	15.6
8.8	9.8	10.8	11.8	12.8	13.8	14.8	15.8

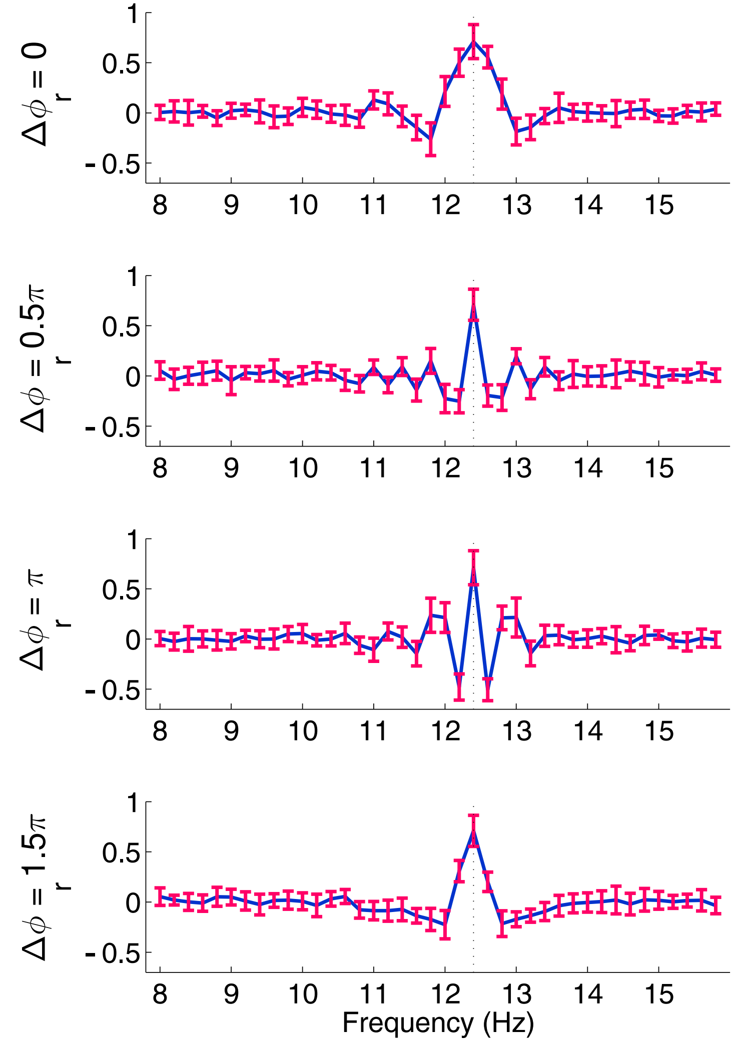
Freq. (Hz)

Integrating phase

>> HIGH SPEED BCI

8.0 / 0.00	9.0 / 1.75	10.0 / 1.50	11.0 / 1.25	12.0 / 1.00	13.0 / 0.75	14.0 / 0.50	15.0 / 0.25
8.2 / 0.35	9.2 / 0.10	10.2 / 1.85	11.2 / 1.60	12.2 / 1.35	13.2 / 1.10	14.2 / 0.85	15.2 / 0.60
8.4 / 0.70	9.4 / 0.45	10.4 / 0.20	11.4 / 1.95	12.4 / 1.70	13.4 / 1.45	14.4 / 1.20	15.4 / 0.95
8.6 / 1.05	9.6 / 0.80	10.6 / 0.55	11.6 / 0.30	12.6 / 0.05	13.6 / 1.80	14.6 / 1.55	15.6 / 1.30
8.8 / 1.40	9.8 / 1.15	10.8 / 0.90	11.8 / 0.65	12.8 / 0.40	13.8 / 0.15	14.8 / 1.90	15.8 / 1.65

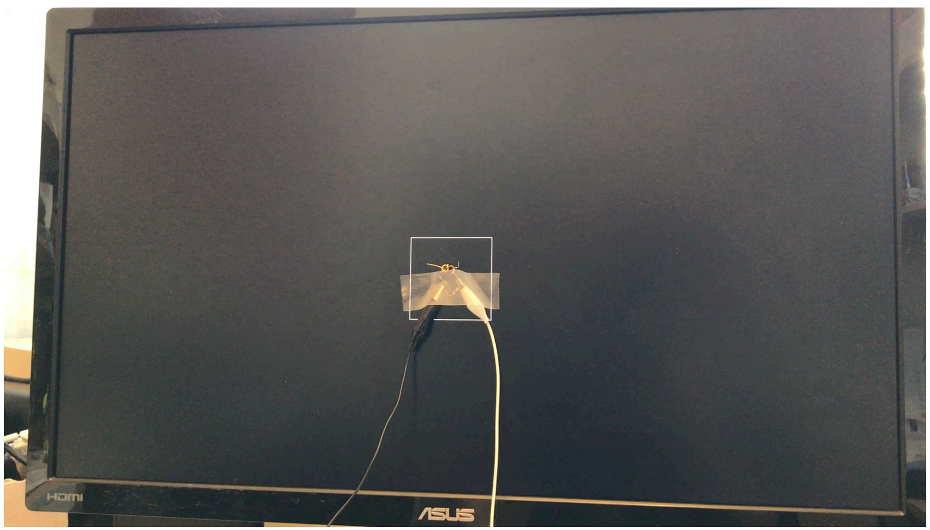
Freq. (Hz) / Phase (π)

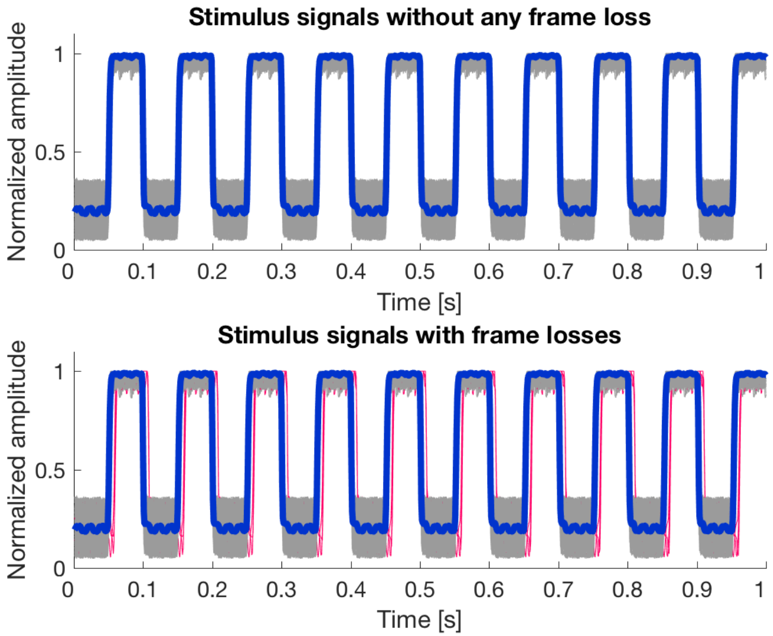


Chen et al., *Proc. Natl. Acad. Sci. USA*, 2015

Stability test of stimulation

- Stability of the stimulation MUST be tested before experiments to make sure if the stimulation is precise.
- Our laboratory uses a phototransistor to measure luminance changes.





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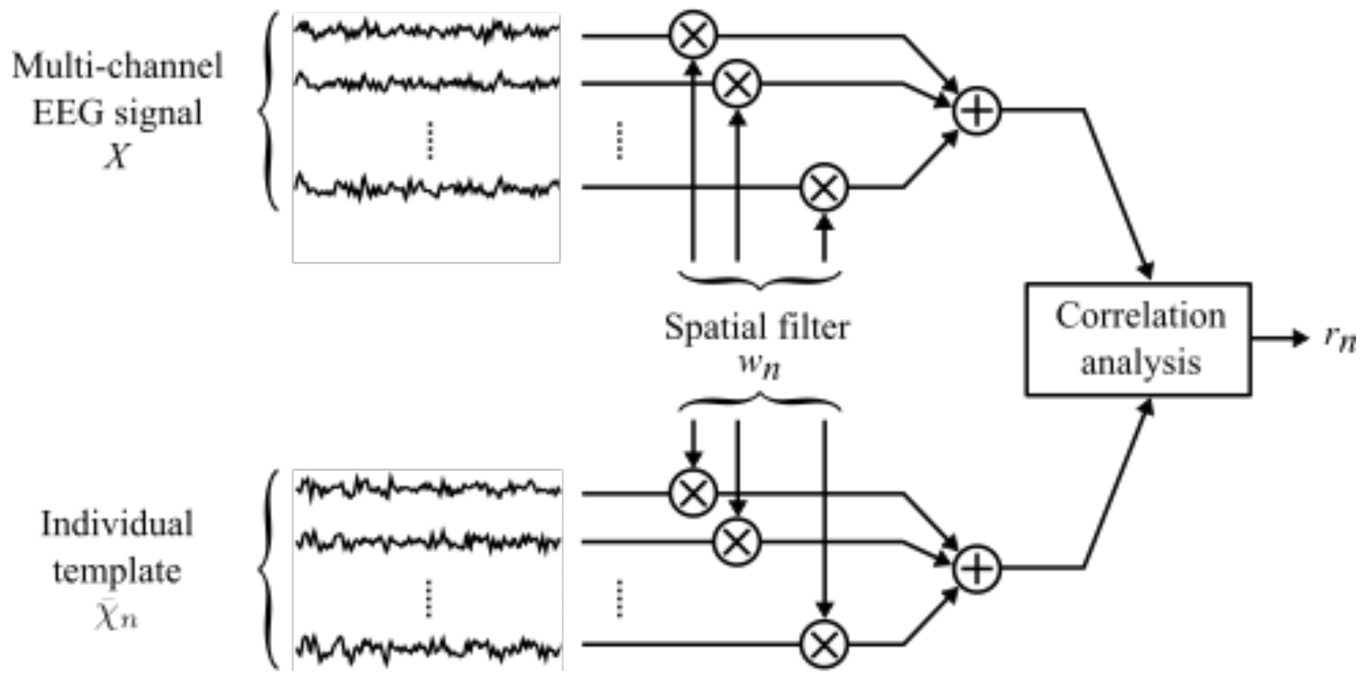
Template matching-based method

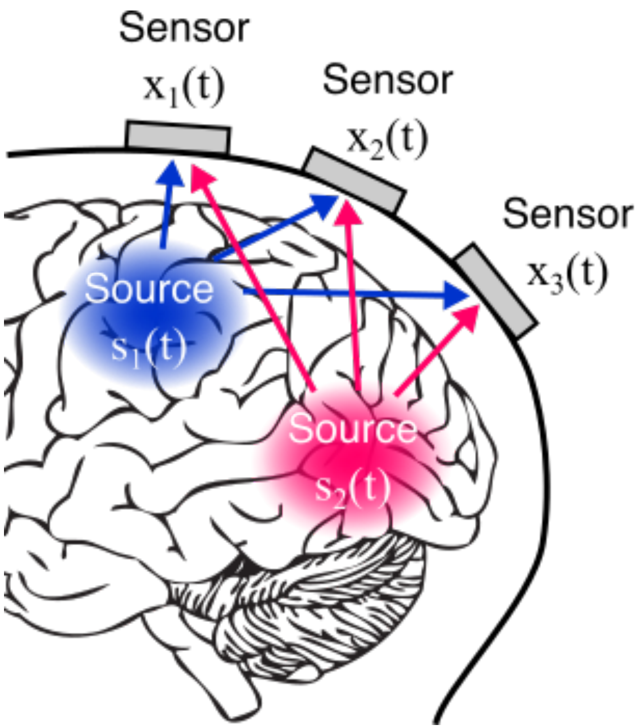
- Correlation between scalp EEG signals and individual templates after spatial filtering.
- Individual template can be obtained by averaging training data across trials.



Nakanishi et al., *Int. J. Neural Syst.*, 2014

EEG mixture model

- Scalp EEG recordings can be modeled as instantaneous linear combination of source signals.



$$\begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \end{bmatrix} = \begin{bmatrix} a_{1,1} & a_{1,2} \\ a_{2,1} & a_{2,2} \\ a_{3,1} & a_{3,2} \end{bmatrix} \begin{bmatrix} s_1(t) \\ s_2(t) \end{bmatrix}$$

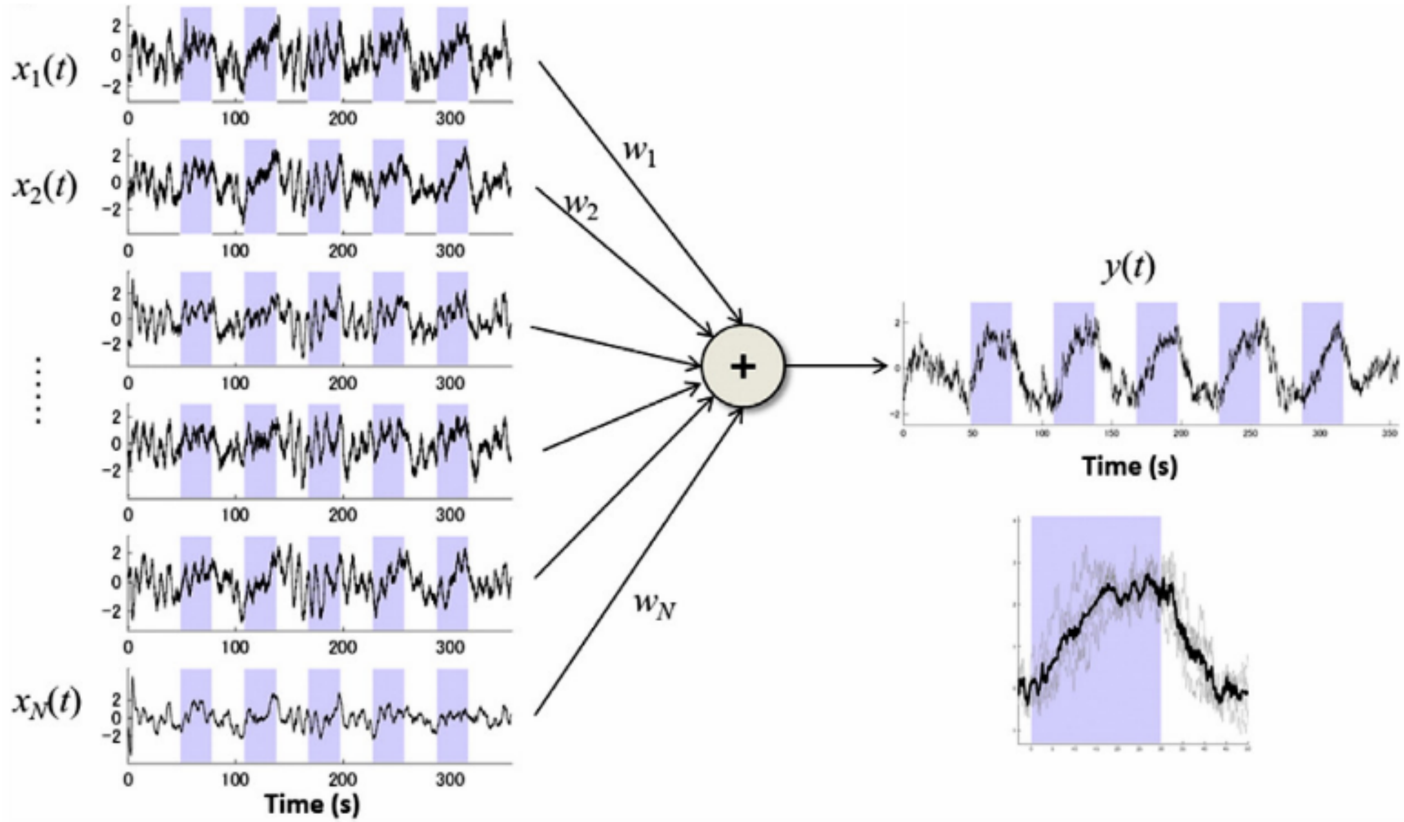
$$\Leftrightarrow \mathbf{x} = \mathbf{A}\mathbf{s}$$

- Source signals can be estimated/reconstructed as follows:

$$\boldsymbol{y} = \boldsymbol{W}\boldsymbol{x} = \boldsymbol{W}\boldsymbol{A}\boldsymbol{s} = \boldsymbol{s} \ \ (when\ \boldsymbol{W}\boldsymbol{A} = 1)$$

TRCA-based spatial filtering

- Task-related component analysis (TRCA) finds a task-related component from multi-dimensional signals by applying a linear coefficient which maximizes the reproducibility across trials.



Tanaka et al., *NeuroImage,* 2013

Problem setting for TRCA

- Two source signals are assumed: 1) task-related signal $s(t) \in \mathbb{R}$; 2) task-unrelated signal $n(t) \in \mathbb{R}$.

- A linear generative model of observed multi-channel signal $\boldsymbol{x}(t) \in \mathbb{R}^{N_c}$ is assumed as:

$$x_j(t) = a_{1,j}s(t) + a_{2,j}n(t), j = 1,2, \ldots, N_c$$

- The problem is to recover the task-related signal $s(t)$ from a linear sum of observed signals $\boldsymbol{x}(t)$ as:

$$y(t) = \sum_{j=1}^{N_c} w_j x_j(t) = \sum_{j=1}^{N_c} \left(w_j a_{1,j} s(t) + w_j a_{2,j} n(t) \right)$$

- Ideally, the problem has a solution of $\sum_{j=1}^{N_c} w_j a_{1,j} = 1$ and $\sum_{j=1}^{N_c} w_j a_{2,j} = 0$, leading to the final solution $y(t) = s(t)$

Problem solution using TRCA (1/2)

- The problem can be solved by inter-trial covariance maximization.
- The h-th trial of EEG signal and the estimated task-related component are described as $\boldsymbol{x}^{(h)}$ and $y^{(h)}$, $h = 1,2, \ldots, N_t$.
- The covariance between h_1-th and h_2-th trials of y is described as:

$$C_{h_1,h_2} = \mathrm{Cov}\left(y^{(h_1)}, y^{(h_2)}\right) = \sum_{j_1,j_2=1}^{N_c} w_{j_1} w_{j_2} \mathrm{Cov}\left(x_{j_1}^{(h_2)}, x_{j_2}^{(h_2)}\right)$$

- All possible combination of trials are summed as:

$$\sum_{\substack{h_1,h_2=1 \\ h_1 \neq h_2}}^{N_t} C_{h_1,h_2} = \sum_{\substack{h_1,h_2=1 \\ h_1 \neq h_2}}^{N_t} \sum_{j_1,j_2=1}^{N_c} w_{j_1} w_{j_2} \mathrm{Cov}\left(x_{j_1}^{(h_2)}, x_{j_2}^{(h_2)}\right) = \boldsymbol{w}^{\mathrm{T}} \boldsymbol{S} \boldsymbol{w}$$

Problem solution using TRCA (1/2)

- To obtain a finite solution, the variance of $y(t)$ is constrained as:

$$\mathrm{Var}(y(t)) = \sum_{j_1,j_2=1}^{N_c} w_{j_1} w_{j_2} \mathrm{Cov}\left(x_{j_1}, x_{j_2}\right) = \boldsymbol{w}^{\mathrm{T}} \boldsymbol{Q} \boldsymbol{w} = 1$$

- The constrained optimization problem can be solved using the method of Lagrange multiplier as:

$$L(\boldsymbol{w}, \lambda) = \boldsymbol{w}^{\mathrm{T}} \boldsymbol{S} \boldsymbol{w} - \lambda\left(\boldsymbol{w}^{\mathrm{T}} \boldsymbol{Q} \boldsymbol{w} - 1\right)$$

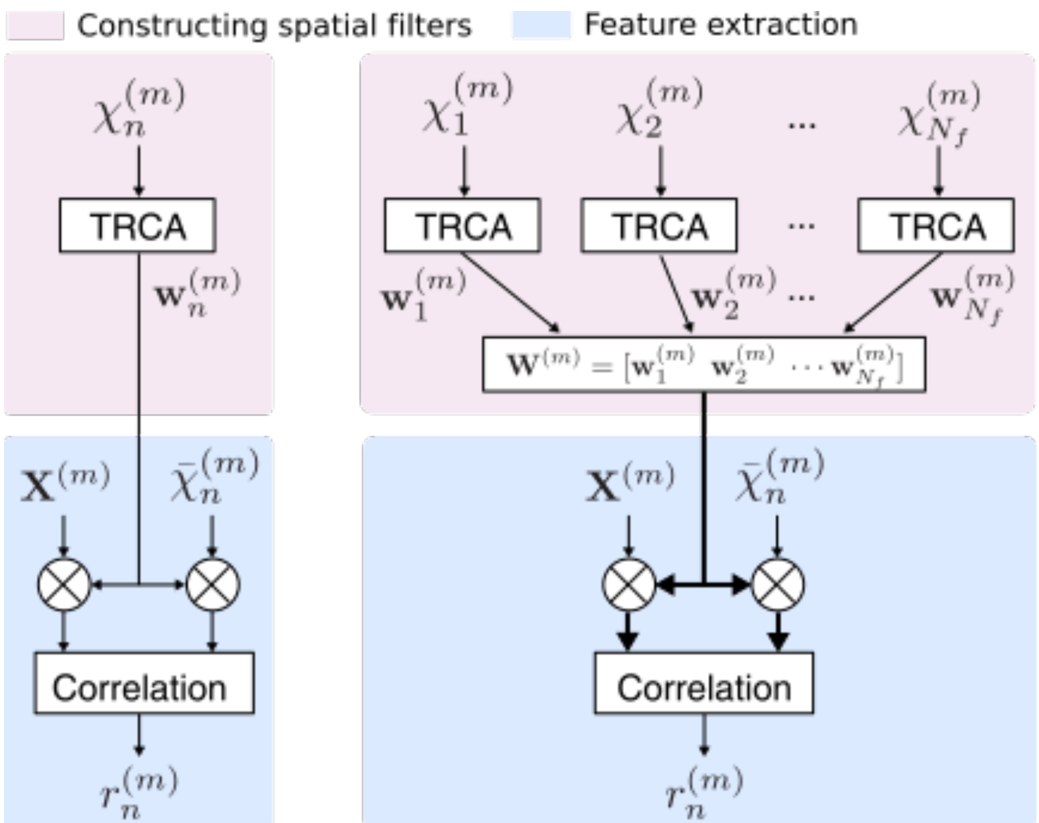
$$\frac{\partial L(\boldsymbol{w},\lambda)}{\partial \boldsymbol{w}} = \boldsymbol{S}\boldsymbol{w} - \lambda\, \boldsymbol{Q}\boldsymbol{w} = 0$$

- The optimal coefficient vector is obtained as the eigenvector of the matrix $\boldsymbol{Q}^{-1}\boldsymbol{S}$.

Framework of target identification

- Target class τ can be identified by the following equation.

$$\tau = \underset{n}{\operatorname{argmax}}\, r_n, n = 1,2,\dots,N_f$$



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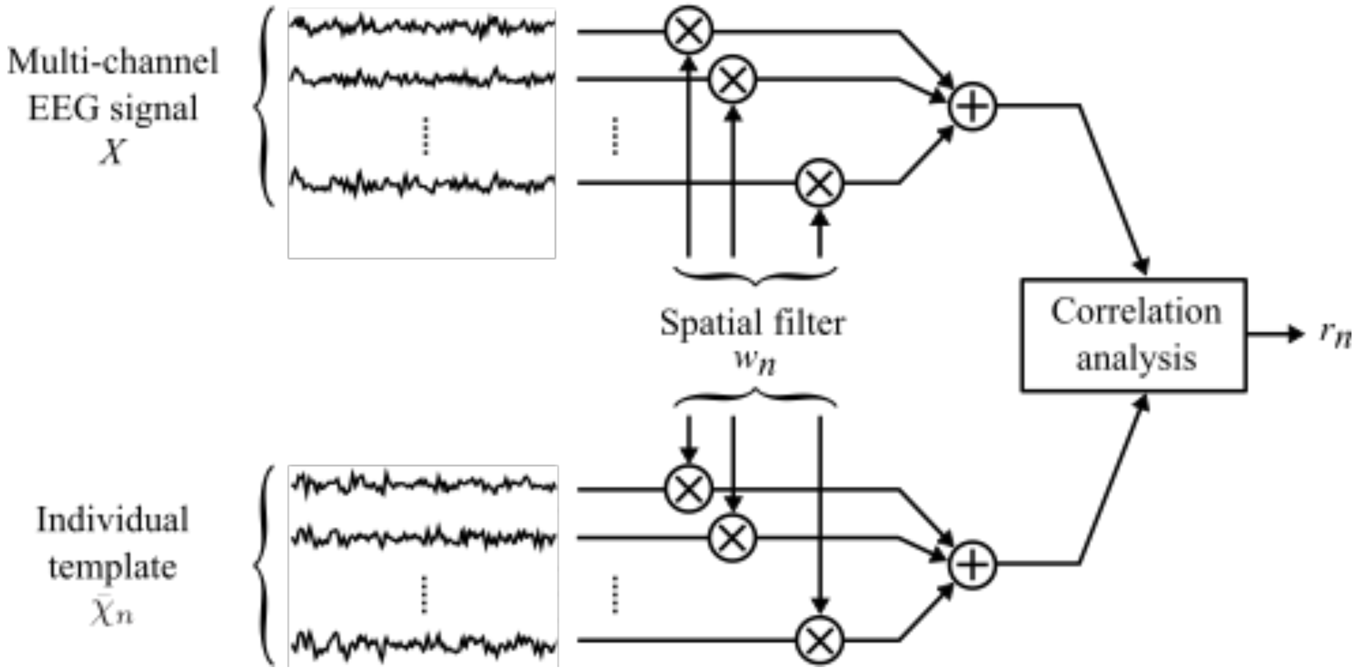
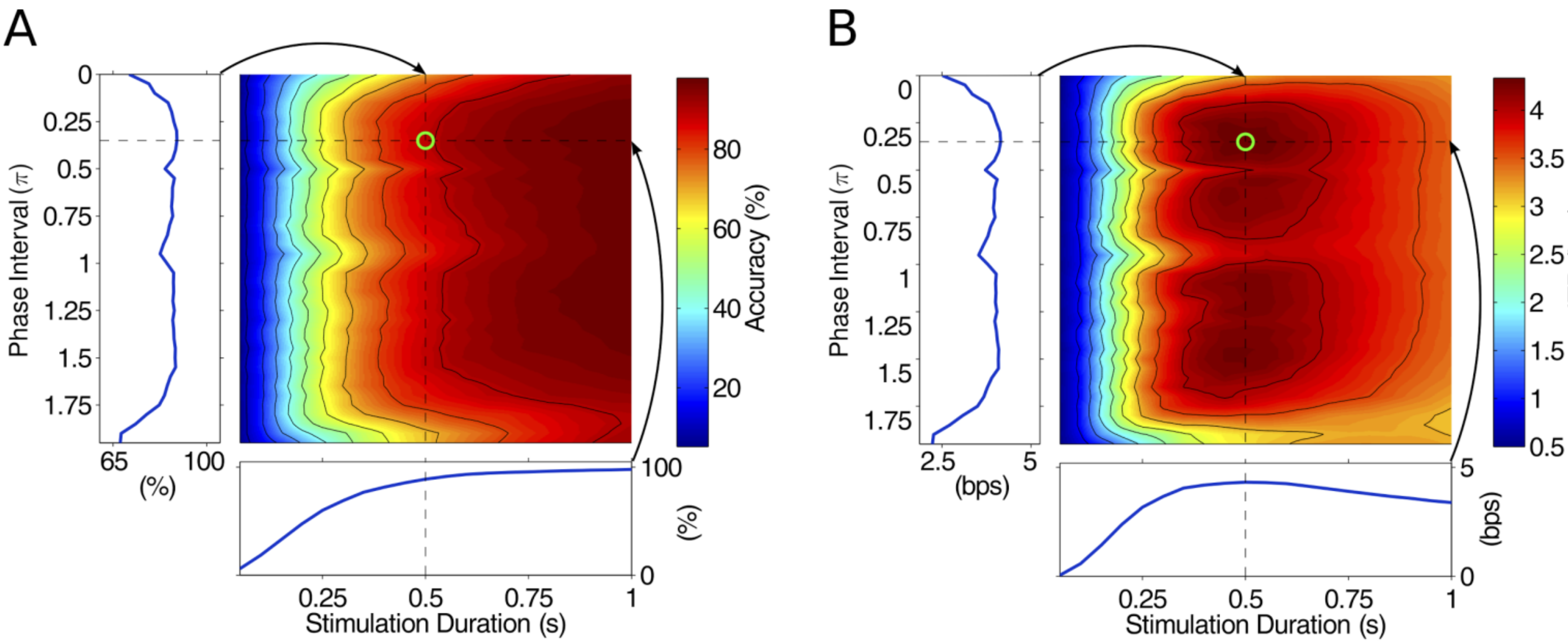


Nakanishi et al., *Int. J. Neural Syst.*, 2014

Joint frequency-phase optimization

30



- Compute accuracy and ITR with offline dataset with different phase intervals
- Results should be different depends on target identification algorithms

Chen et al., *Proc. Natl. Acad. U.S.A.*, 2015

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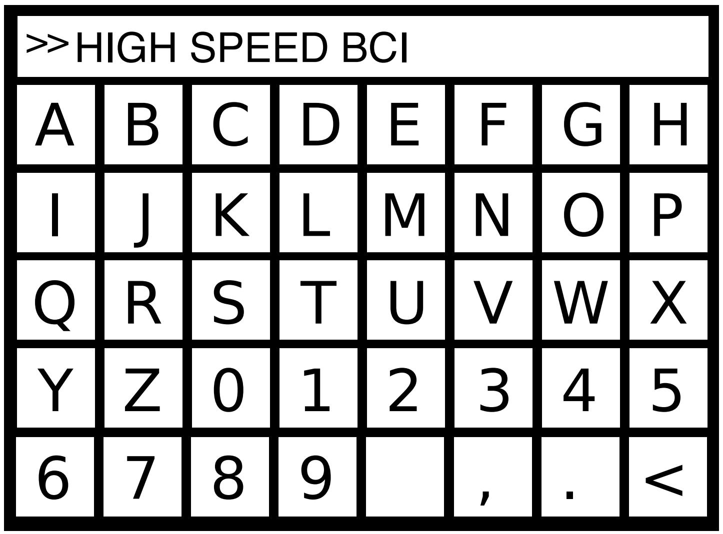
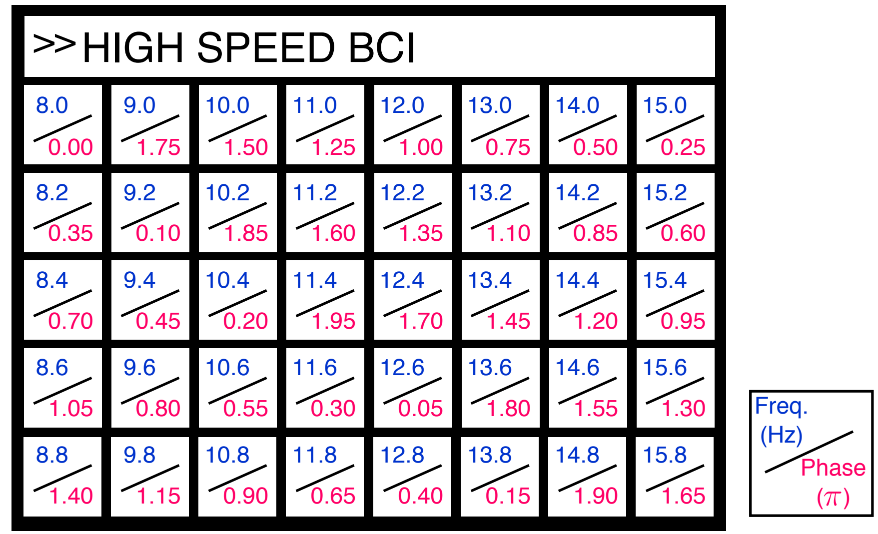
Stimulus design



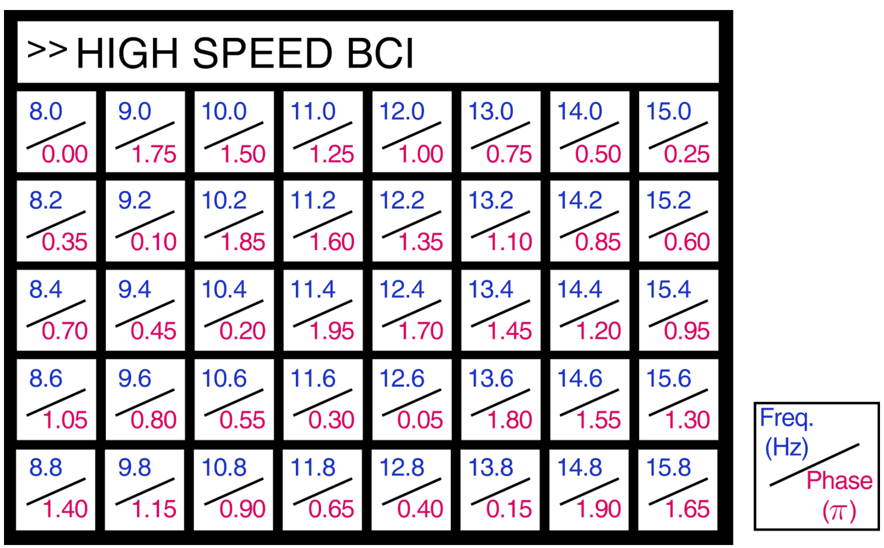


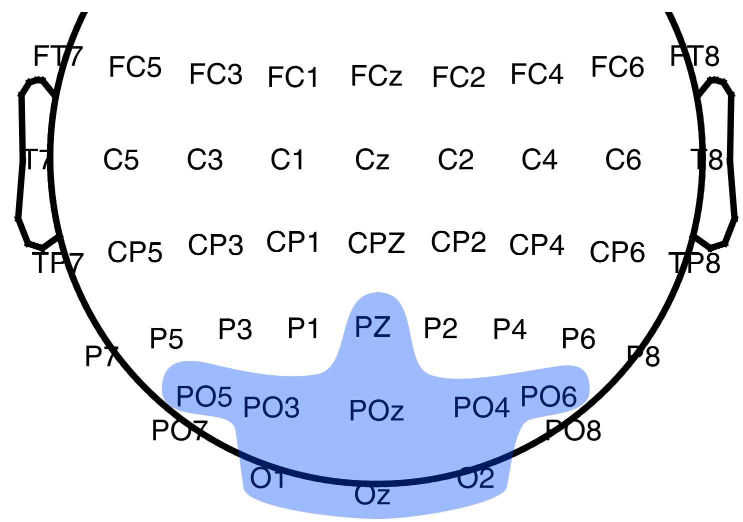
- Stimulus design for a BCI speller
  - 26 English alphabets, 10 digits, 4 symbols
  - Frequency range : 8 – 15.8 Hz with an interval of 0.2 Hz
  - Phase range : 0 – 2 π with an interval of 0.35 π

Nakanishi et al., *IEEE Trans. Biomed. Eng.*, 2017 (In press)

Dataset

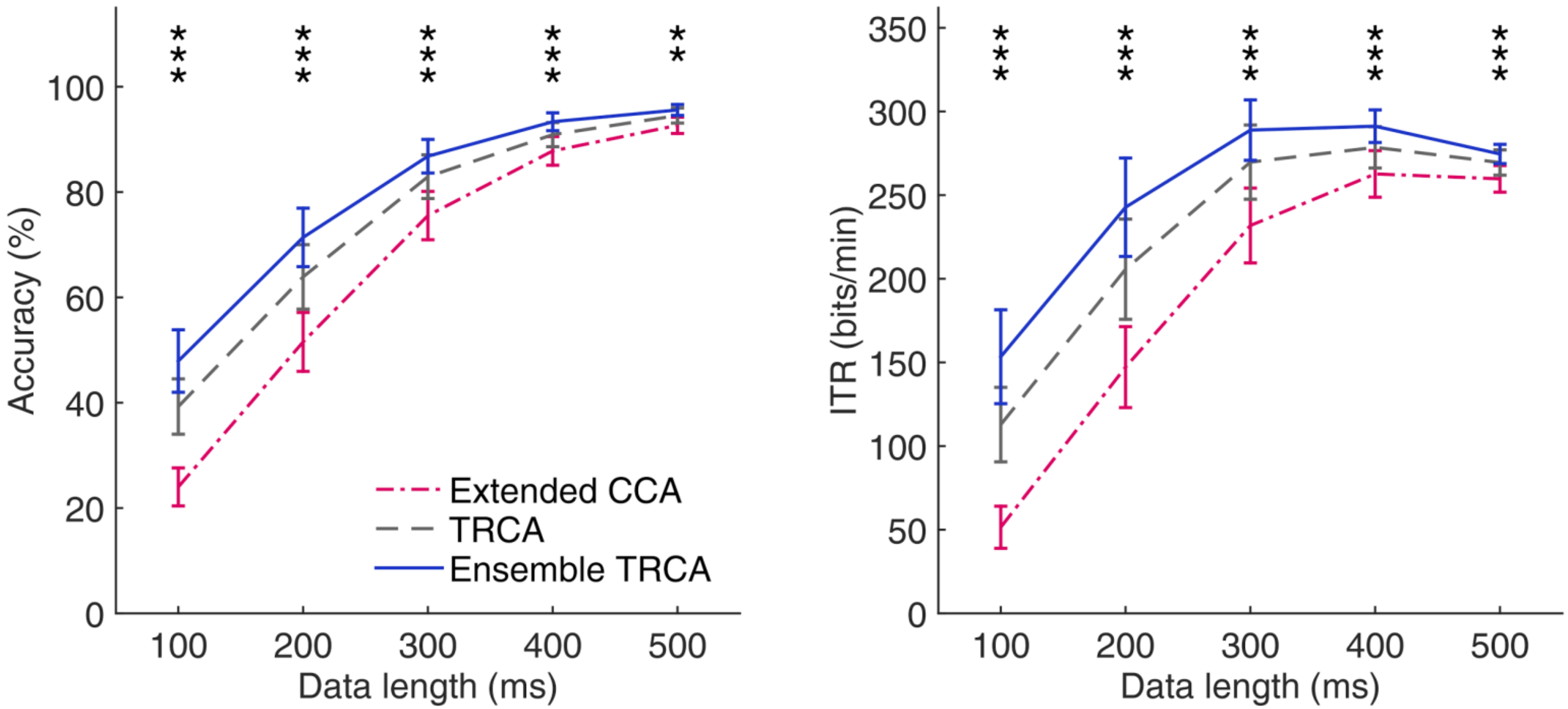
- 40-target visual stimuli were presented on a 23.6-inch LCD monitor.
- EEG data were recorded from 12 subjects with 9 electrodes over parietal and occipital areas.
- The experiment consisted of 12 blocks, in which the subjects were asked to gaze at one of the stimuli indicated by the stimulus program in a random order for 0.5 s followed by a 0.5-s short break.





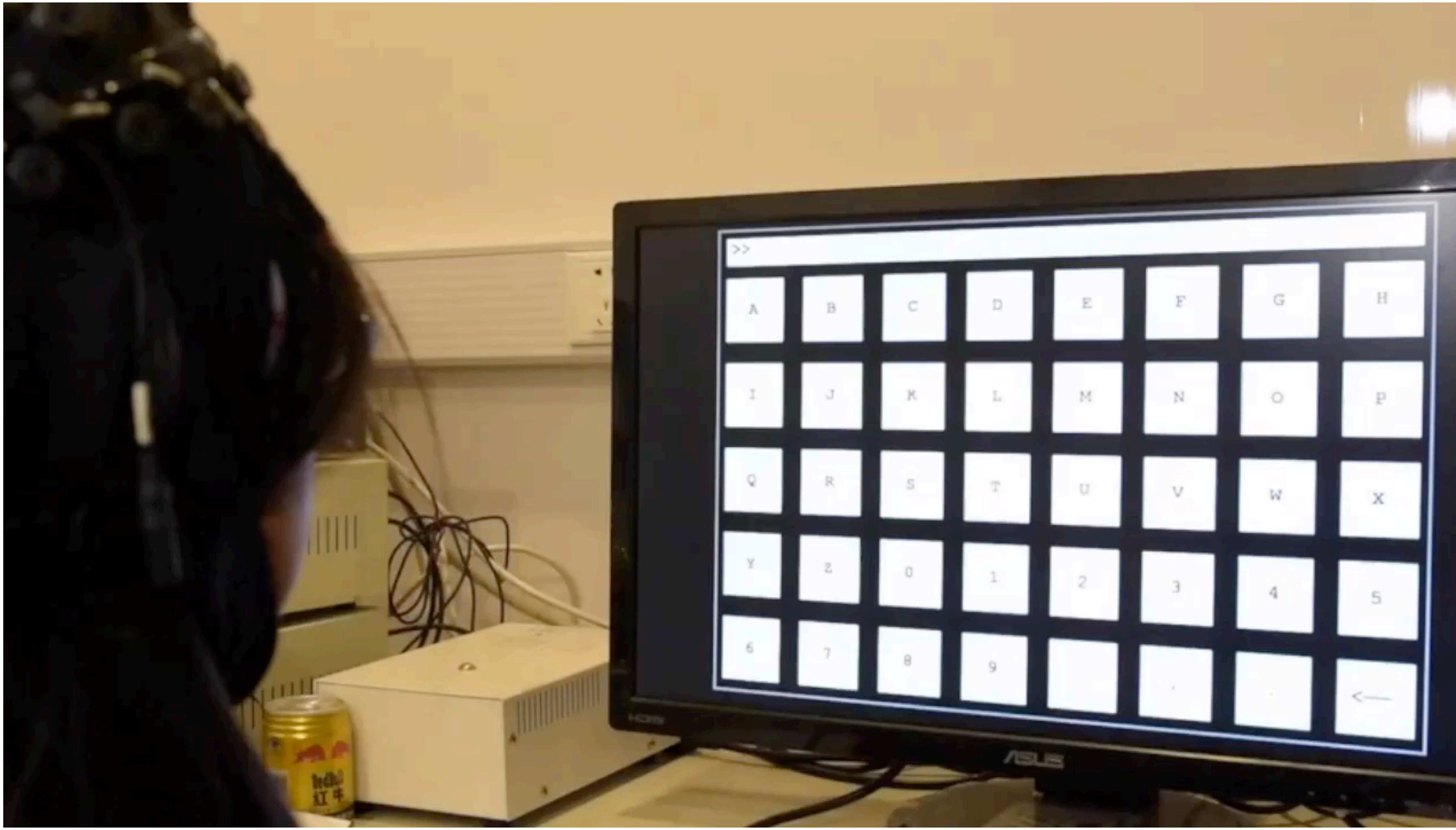
Chen et al., *Proc. Natl. Acad. U.S.A.*, 2015

Results of offline analysis



- The accuracy was estimated using a leave-one-out cross validation (LOOCV).
- There was significant main effects of the target identification algorithms in the accuracy and ITR ($p<0.05$).

An SSVEP-based BCI speller



Nakanishi et al., *IEEE Trans. Biomed. Eng.*, 2017 (In press)

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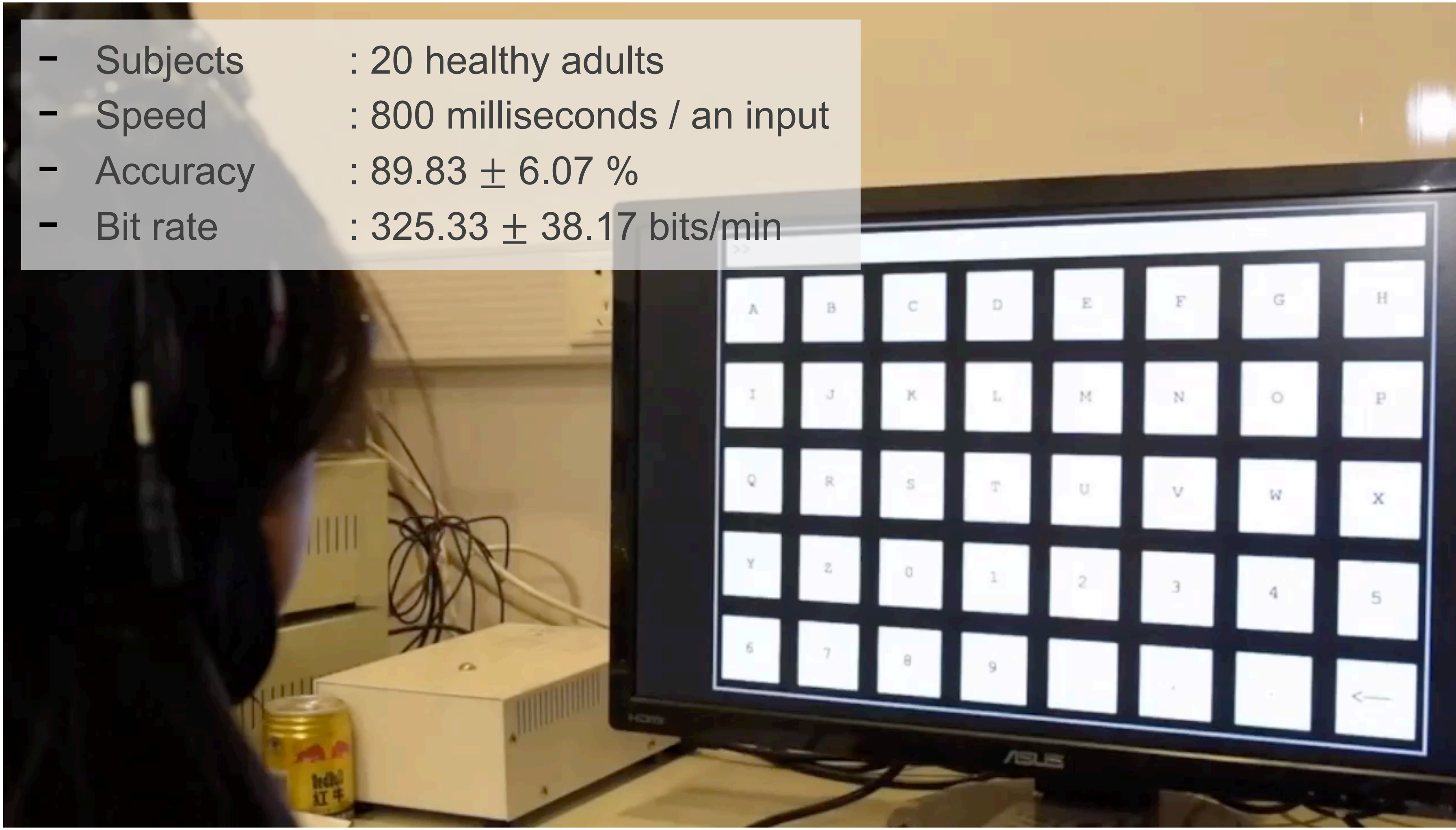

- Subjects : 20 healthy adults
- Speed : 800 milliseconds / an input
- Accuracy : 89.83 $\pm$ 6.07 %
- Bit rate : 325.33 $\pm$ 38.17 bits/min

Nakanishi et al., *IEEE Trans. Biomed. Eng.*, 2017 (In press)

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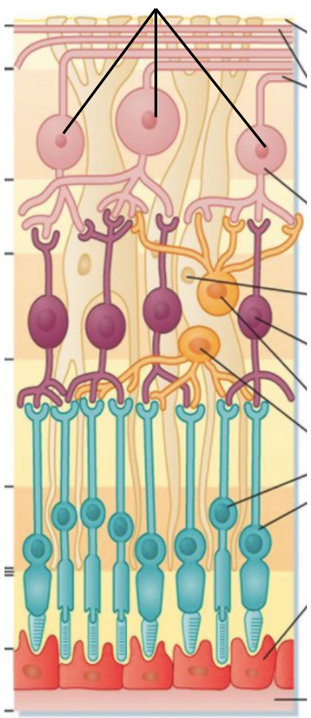
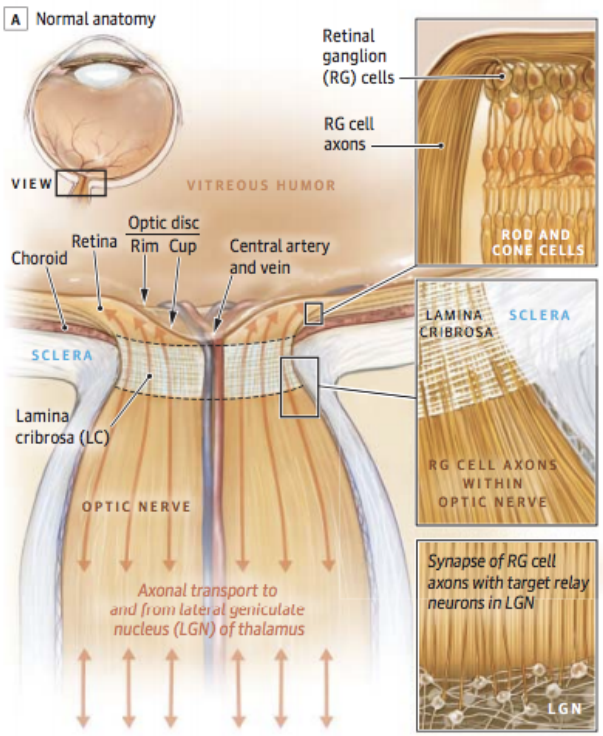
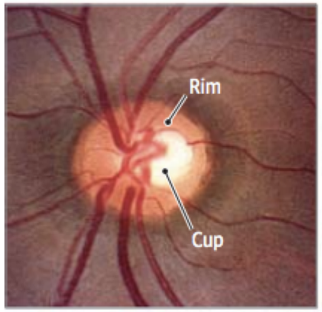
Glaucoma -青光眼 / 緑内障

- Glaucoma is a group of progressive optic neuropathies characterized by degeneration of retinal ganglion cells.
- Glaucoma is the leading cause of irreversible visual impairment.

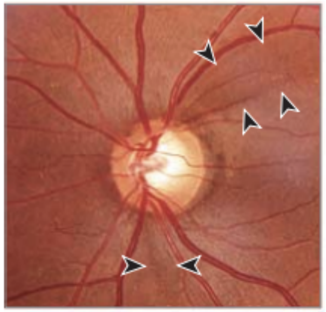
Retinal ganglion cells







Normal optic nerve



Glaucomatous optic nerve

Weinreb, et al., *JAMA*, 2014

Challenges in glaucoma assessment

- **Early detection**

Glaucomatous visual field losses progress without noticeable initial symptoms, resulting frequently in late diagnosis or late detection of progressive damage.

- **Lack of objectivity and portability**

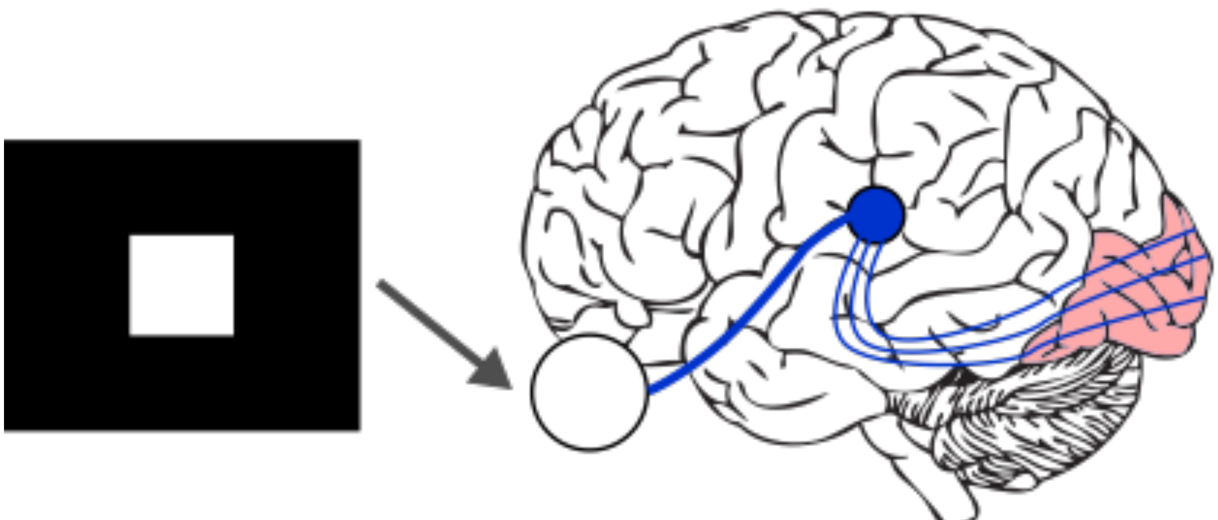
Conventional assessment methods have significant drawbacks such as large test-retest variability, cumbersome clinic-based setting.

A portable, low cost, and objective method for assessing visual impairment in glaucoma is required for early detection.

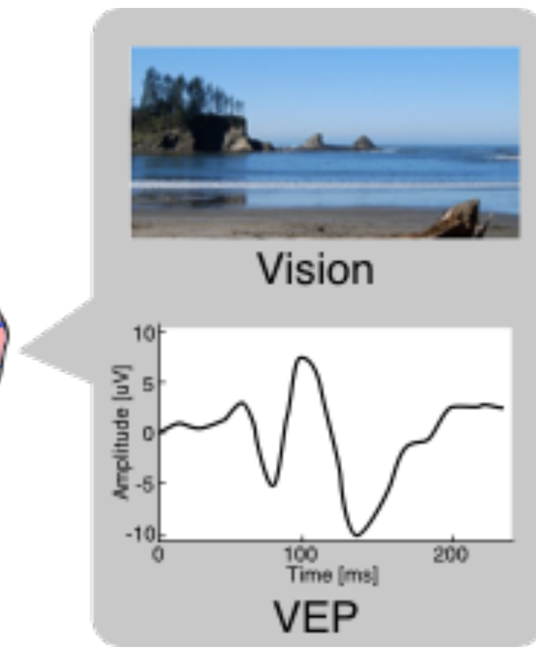
Weinreb, et al., *JAMA,* 2014

Glaucoma assessment using SSVEPs

- Previous studies showed a good correspondence between the results of conventional visual field assessment and the amplitude of SSVEPs.
- Current data recordings are time consuming and uncomfortable for patients due to skin preparation and gel application.



Healthy eye



Hood et al., *Vis. Neurosci.*, 2000

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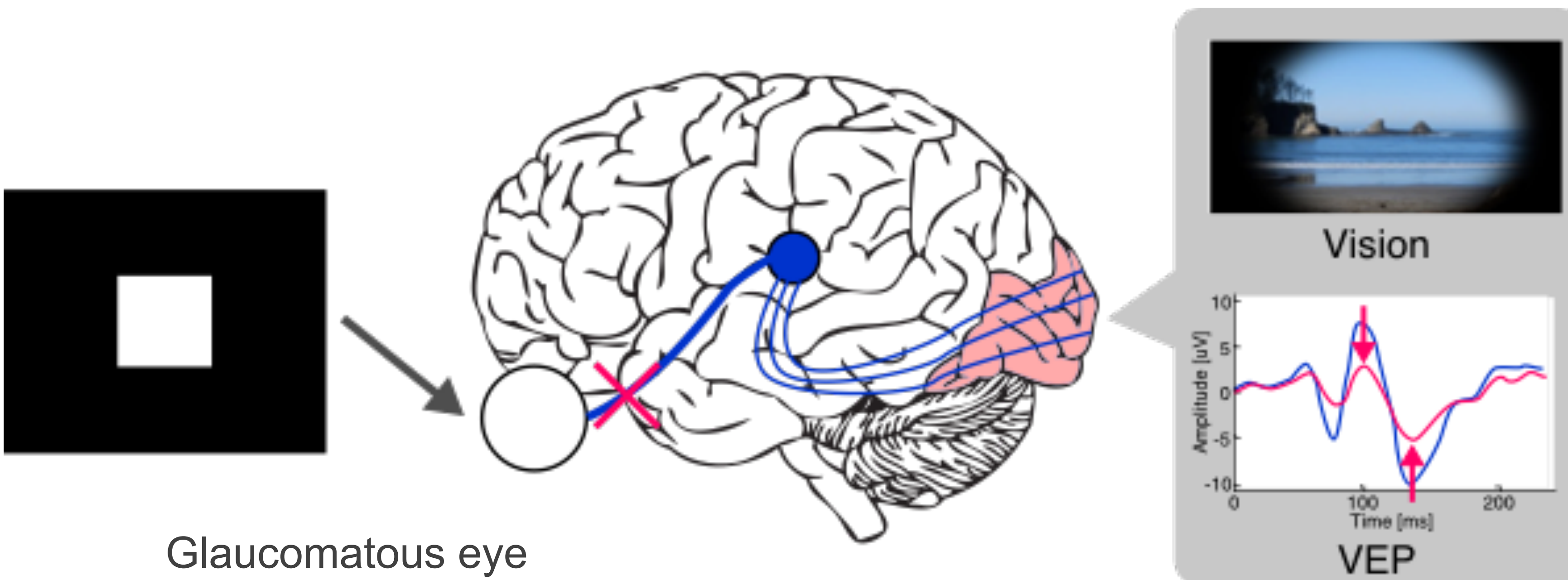
- Current data recordings are time consuming and uncomfortable for patients due to skin preparation and gel application.

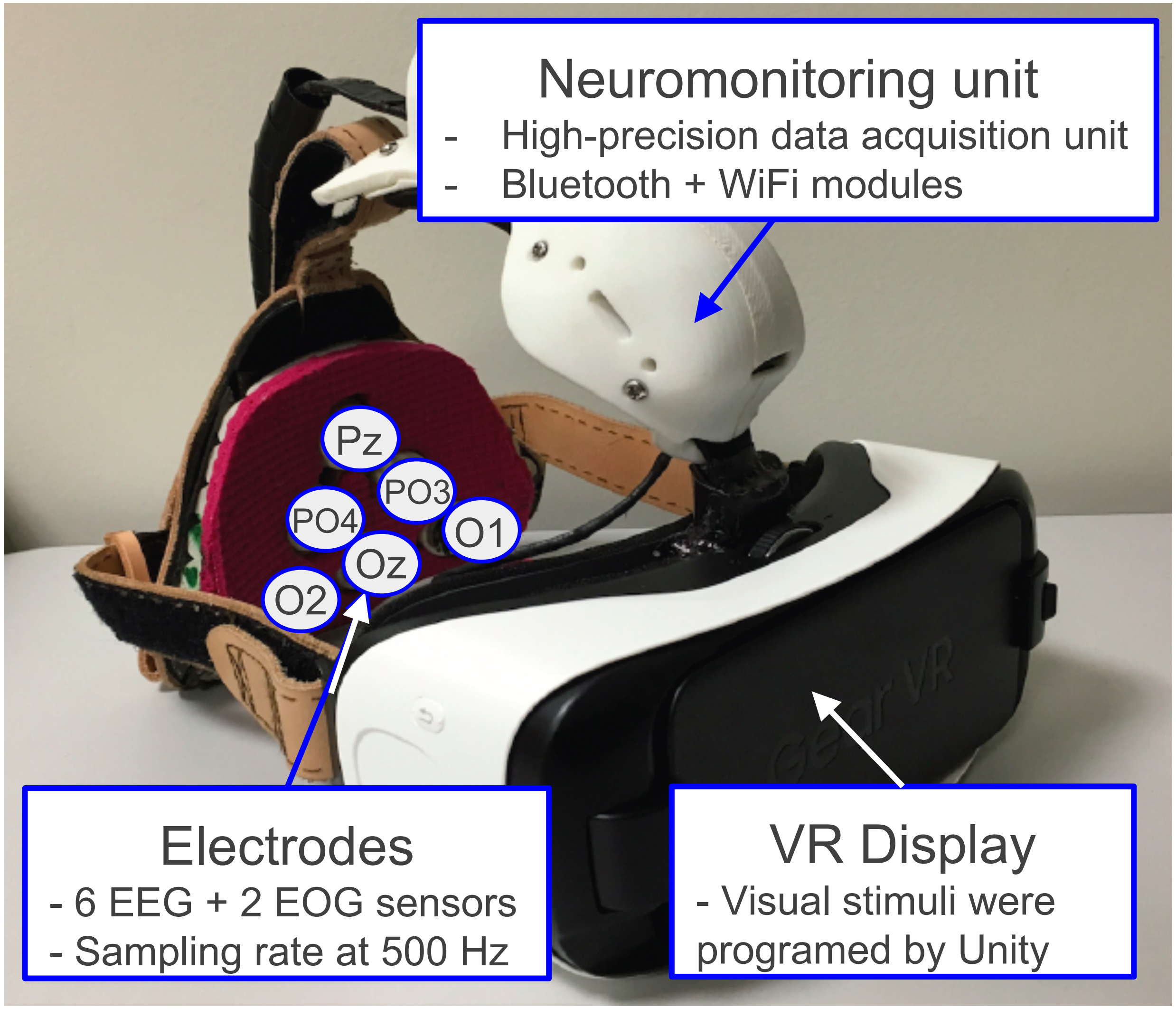


Hood et al., *Vis. Neurosci.*, 2000

The nGoggle: A portable BCI device

Nakanishi et al., *JAMA Ophthalmol*. 2017

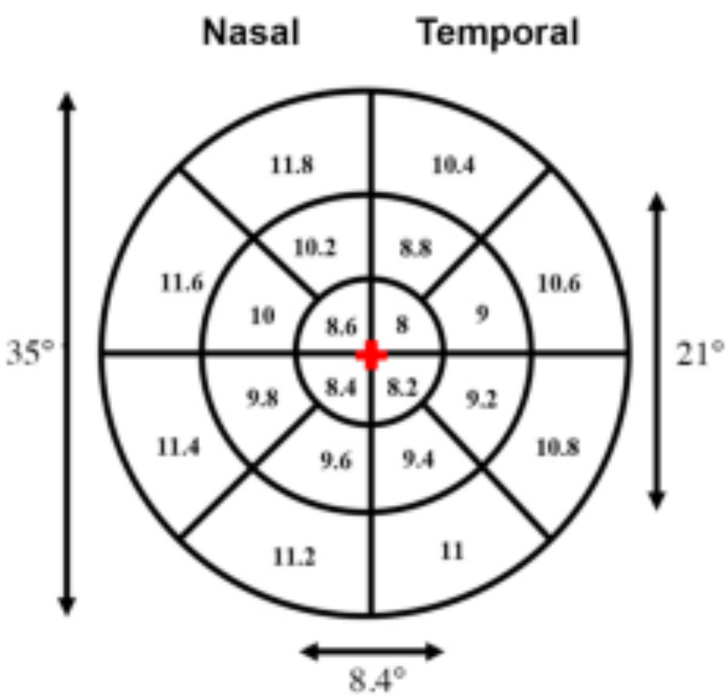
The nGoggle: A portable BCI device



Nakanishi et al., *JAMA Ophthalmol*. 2017

Stimulus design

- Visual stimuli eliciting multi-focal SSVEPs in 20 sectors over the 35-degree field of vision were presented on the nGoggle's display.
- Stimulus frequencies: 8 - 11.8 Hz with an interval of 0.2 Hz



Nakanishi et al., *JAMA Ophthalmol*. 2017

Demographical characteristics

	Glaucoma (n = 62 eyes of 33 subjects)	Control (n = 30 eyes of 17 subjects)	P-Value
Age, years	68.2 ± 11.0	66.1 ± 9.9	0.57
Gender, female, n (%)	8 (47)	16 (48)	0.92
Race, n (%)			0.50
White	19 (58)	9 (53)	
Black	12 (36)	8 (47)	
Asian	2 (6)	0 (0)	
SAP 24-2 MD, dB	-4.0 (-12.7 to -1.8)	-0.6 (-2.4 to 1.0)	< 0.001
SAP 24-2 PSD, dB	4.7 (2.2 to 9.9)	1.9 (1.4 to 3.0)	< 0.001
SSVEP CCA ρ	0.289 ± 0.020	0.334 ± 0.024	< 0.001

* SAP: Standard automated perimetry; MD: Mean deviation; PSD: Pattern standard deviation; CCA: Canonical correlation analysis

Nakanishi et al., *JAMA Ophthalmol*. 2017

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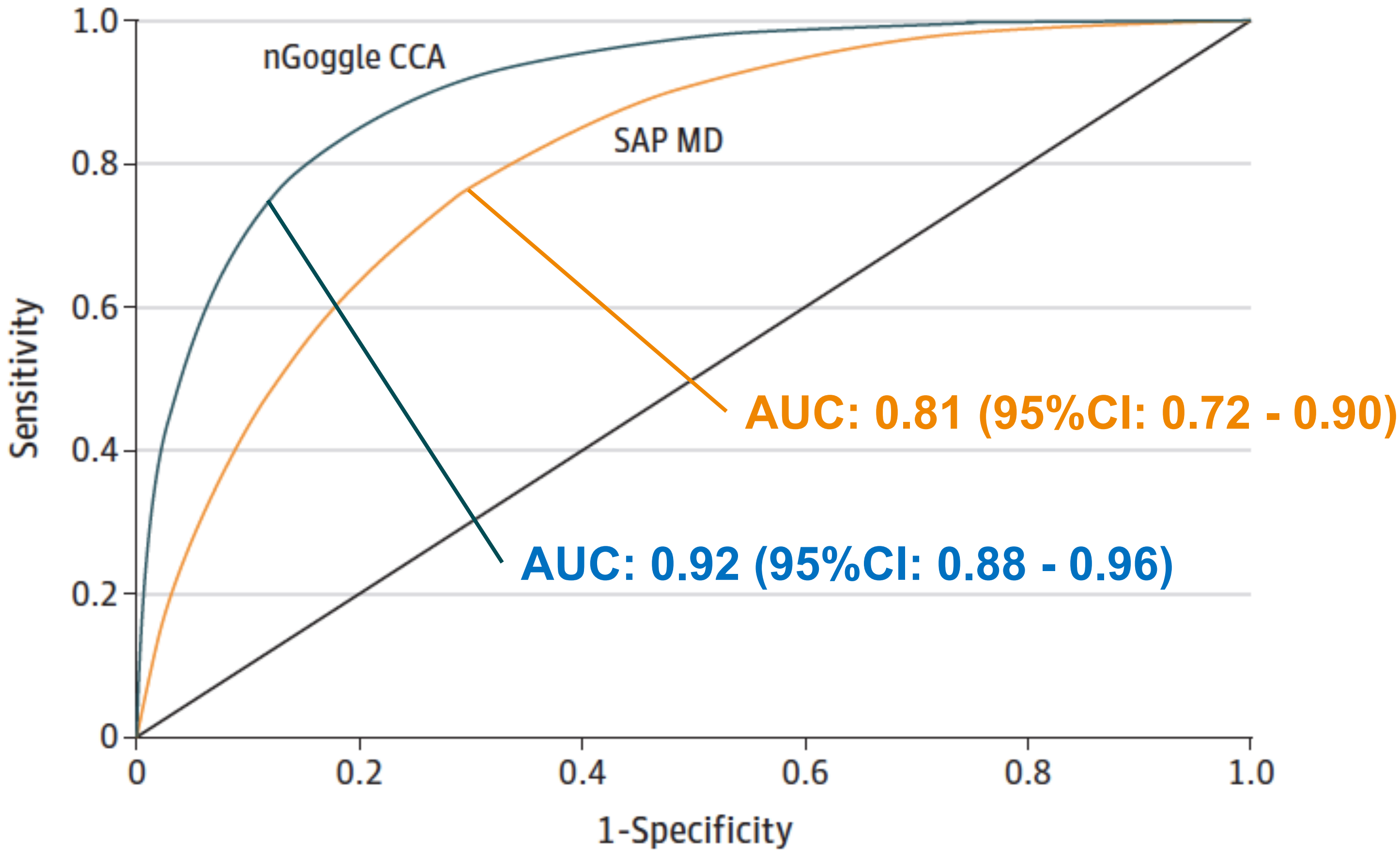
Nakanishi et al., *JAMA Ophthalmol*. 2017

Diagnostic ability

Figure 2. Receiver Operating Characteristic Curves for the Global nGoggle Parameter and Standard Automated Perimetry Mean Deviation



Nakanishi et al., *JAMA Ophthalmol*. 2017

Outline

1. **Introduction**
   - Brain-computer interface (BCI)
   - Steady-state visual evoked potentials
   - BCI based on SSVEPs
2. **Material and Methods**
   - Display-based stimulus presentation
   - Target identification algorithms
3. **Applications**
   - A high-speed BCI speller
   - (Assessment of visual impairment in glaucoma)
4. **Summary**

Summary

- **Designing an SSVEP-based BCI**
  - Jointly optimizing parameters in visual stimuli and target identification algorithm
- **Display-based stimulus presentation**
  - can easily change the stimulus configuration
  - allows to render a large number of visual stimuli on a display
  - encourage a variety of applications based on SSVEPs
- **Template-based target identification**
  - TRCA can significantly improve the SNR of SSVEPs
- **Brain-computer interface based on SSVEPs**
  - succeeded in spelling characters, digits, and symbols
  - achieved the highest information transfer rate to date

Future works

- **Display-based stimulation**
  - Reducing visual fatigues by employing imperceptible stimuli (i.e., High frequency range over 40 Hz)
- **SSVEP BCI speller**
  - Implementing a truly portable system (i.e., Mobile / Head-mounted displays)
- **Glaucoma assessment**
  - Sector-by-sector analysis for visual field assessment
  - Testing different types of glaucoma population (e.g., early-stage glaucoma)

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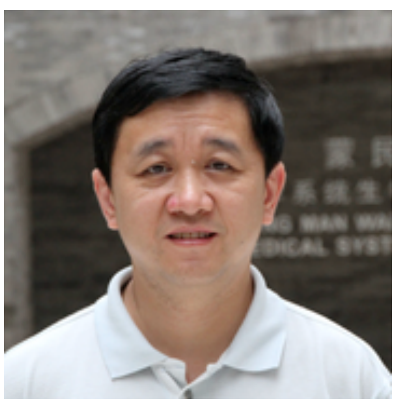

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Duke Univ., USA

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Thank you for your kind attention

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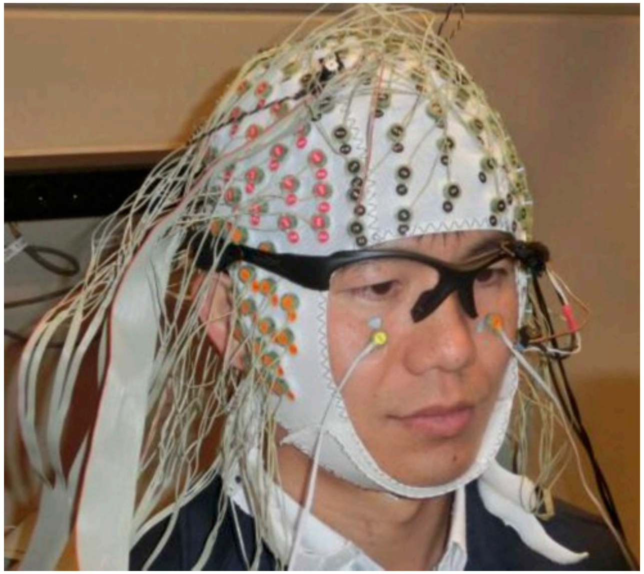
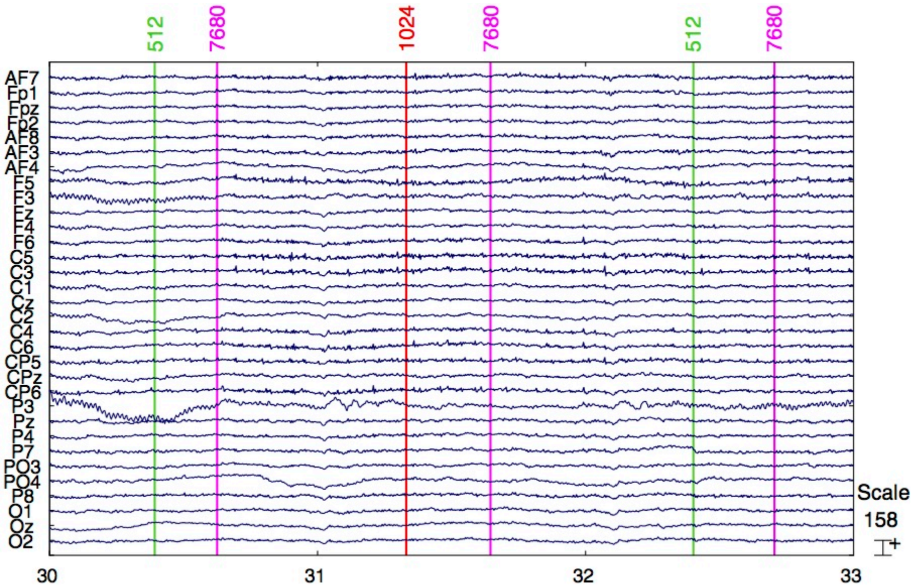
Appendix

Electroencephalogram (EEG)

- EEG is the measurement of brain electrical fields via electrodes placed on the scalp, which might be associated with particular sensory or cognitive states.
- EEG is one of the most important non-invasive brain imaging tools in neuroscience and clinic.

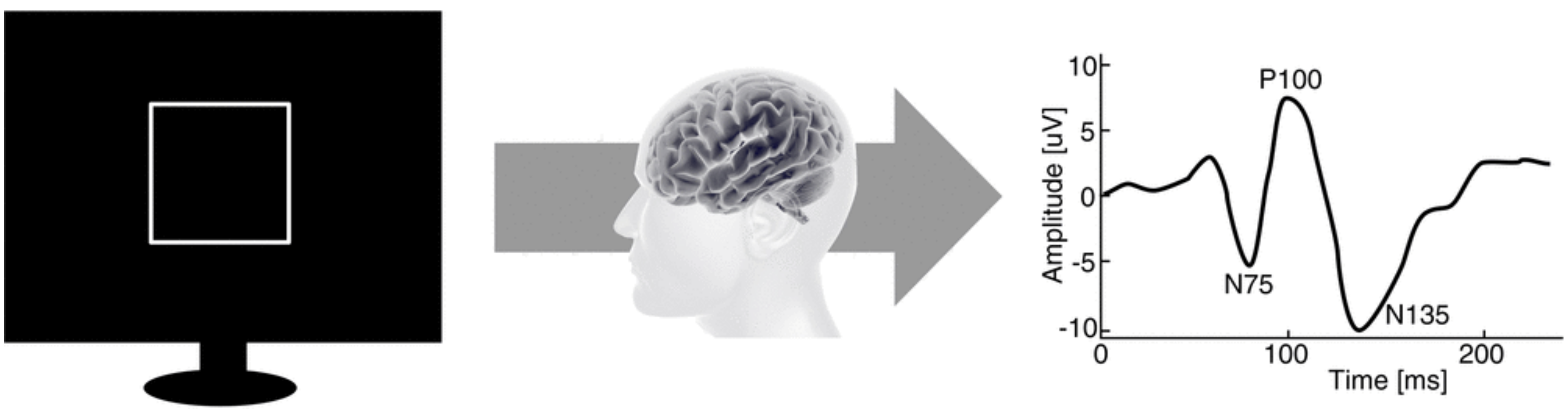




Cohen et al., *Trends Neurosci*. 2017

Visual Evoked Potentials (VEPs)

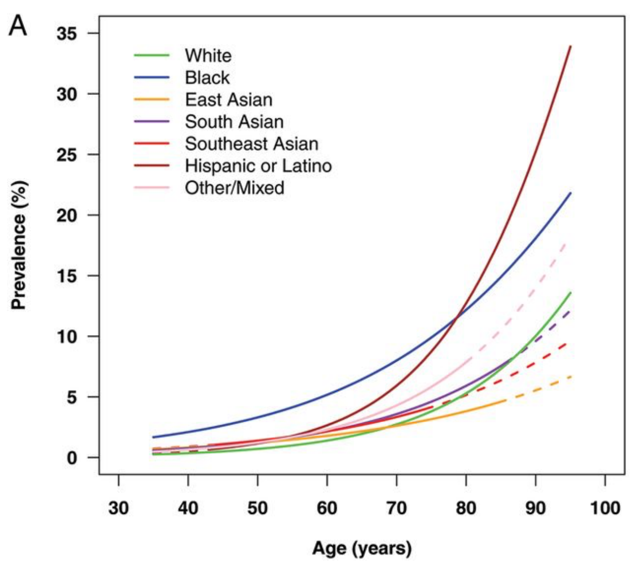
- VEPs are brain's electrical responses to visual stimuli such as flashing lights or sudden changes in image patterns.
- VEPs consist of positive and negative deflections in EEG signals observed in the occipital scalp area over primary visual cortex.



Vialatte et al., *Prog. Neurobiol.* 2010

Glaucoma prevalence

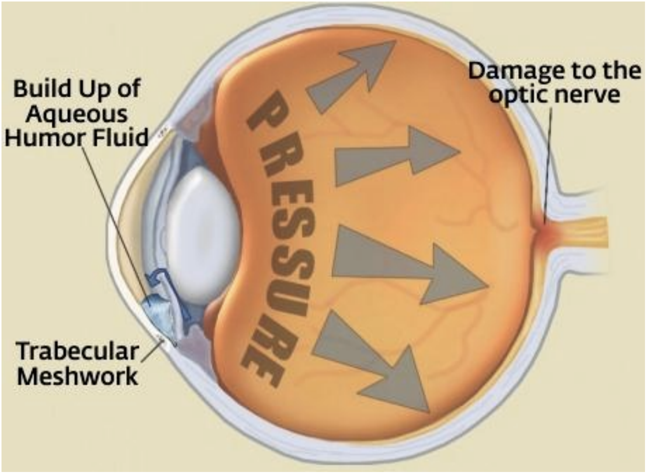
- Glaucoma is the leading cause of irreversible visual impairment in the world.
- Glaucoma affects more than 70 million people worldwide with approximately 10 % being bilaterally blind.

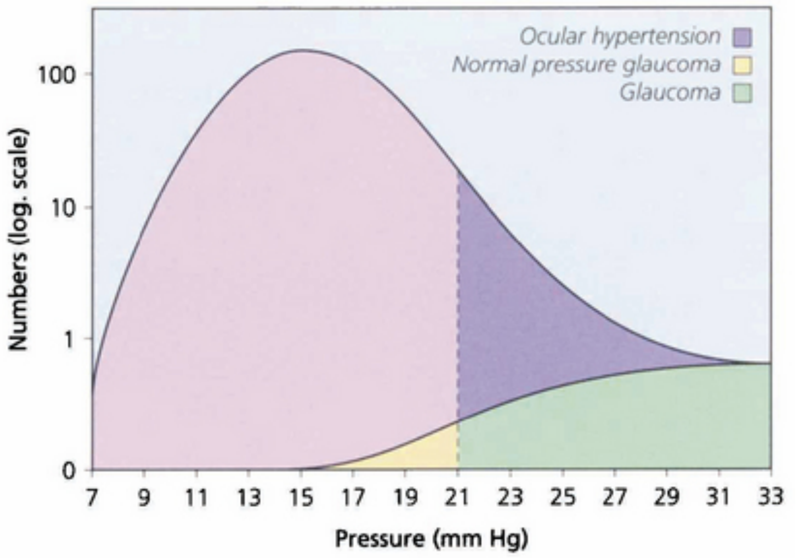


Kapetanakis V.V. et al., *Br. J. Opthalmol.*, 2015

What causes glaucoma?

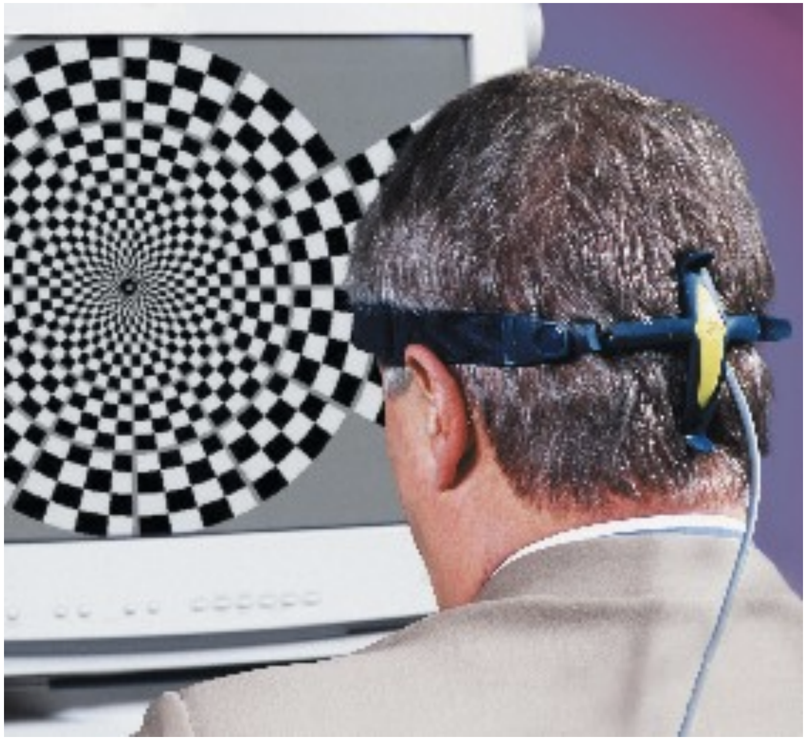
- There are many theories, but the exact cause is unknown.
  - ✓ High intraocular pressure (IOP)
  - ✓ Inefficient eye's drainage system
  - ✓ Poor blood flow
- Since glaucoma is irreversible, early diagnosis is crucial.

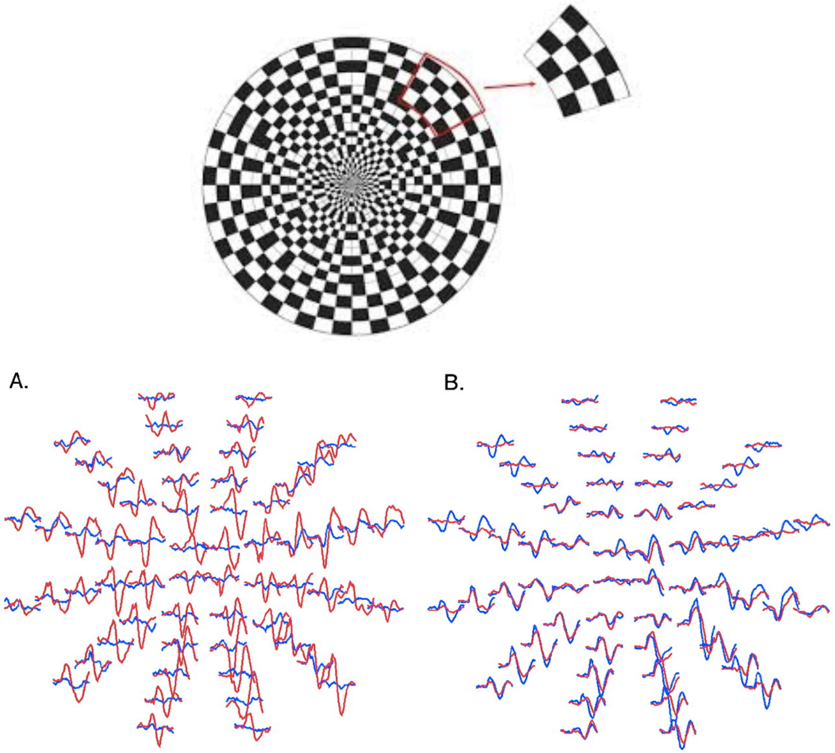




Diagnosis of glaucoma (2/2)

- Multifocal visual evoked potentials (mfVEPs)-based objective assessment





Hood et al., *Vis. Neurosci.*, 2000

Challenges

- Glaucomatous visual field losses progress without noticeable initial symptoms, resulting frequently in late diagnosis or late detection of progressive damage.
- Conventional assessment methods have significant drawbacks such as large test-retest variability, cumbersome clinic-based setting.

A portable, low cost, and objective method for assessing visual impairment in glaucoma is required.

The nGoggle

- We recently developed the nGoggle, a portable device for objective assessment of visual field loss based on multifocal steady-state visual evoked potentials (mfSSVEPs).

Research

JAMA Ophthalmology | Original Investigation

Detecting Glaucoma With a Portable Brain-Computer Interface for Objective Assessment of Visual Function Loss

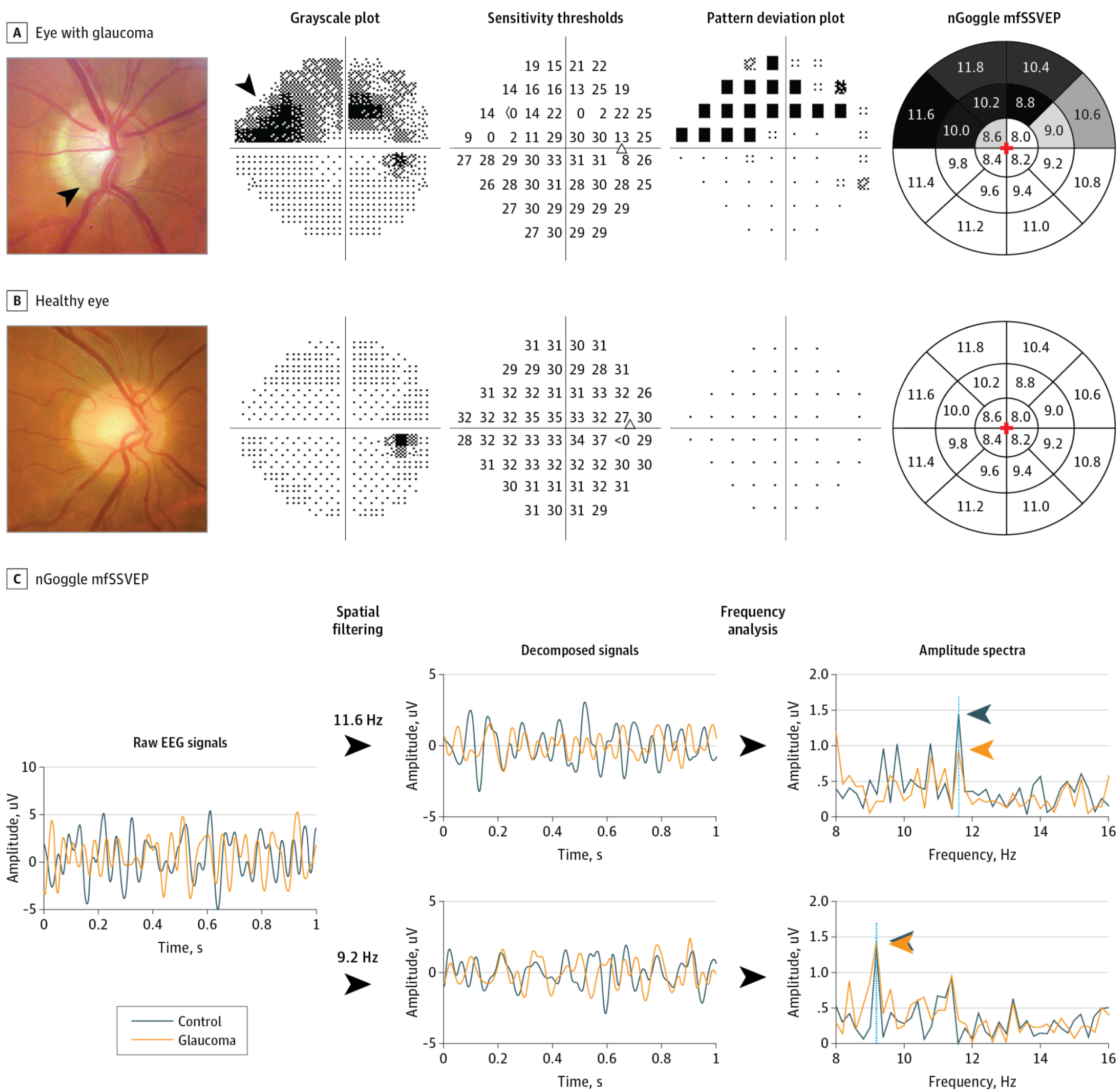
Masaki Nakanishi, PhD; Yu-Te Wang, PhD; Tzyy-Ping Jung, PhD; John K. Zao, PhD; Yu-Yi Chien, PhD; Alberto Diniz-Filho, MD; Fabio B. Daga, MD; Yuan-Pin Lin, PhD; Yijun Wang, PhD; Felipe A. Medeiros, MD, PhD

Nakanishi et al., *JAMA Ophthalmol*. 2017

Participants

- 62 eyes of 33 patients with glaucoma and 30 eyes of 17 healthy patients were tested with the nGoggle and performed SAP SITA 24-2.
- Glaucoma were diagnosed based on optic disc stereographs.

Results from the nGoggle and SAP



Reproducibility

- The reproducibility of measurements obtained by the nGoggle was investigated in 20 eyes of 10 participants with glaucoma.
- The participants has 3 sessions of measurements separated by weekly intervals between sessions.
- The average intra-class coherence coefficients (ICC) of the global mfSSVEP parameter was 0.92 (95%CI: 0.82 – 0.97), which was greater than 0.75 ($P < 0.001$).

Preperimetric glaucoma

- Many patients can lose a substantial amount of neural tissue despite absence of *detectable* visual field defects in SAP.[3]
- Preperimetric glaucoma (PPG) has been defined as presence of glaucomatous optic neuropathy with normal SAP results.

This study investigated the nGoggle ability in detecting PPG

[3]Sommer, A., et al., *Arch Ophthalmol*. 1991

Participants

- 30 eyes of 20 patients with PPG and 18 eyes of 11 healthy patients were tested with the nGoggle and performed SAP SITA 24-2.
- The patients with PPG were selected based on the presence of GON on optic disc stereophotographs and normal SAP results.

Demographical characteristics

	PPG (n = 30 eyes of 20 subjects)	Control (n = 18 eyes of 11 subjects)	P-Value
Age, years	68.7 ± 10.3	65.1 ± 10.5	0.363
Gender, female, n (%)	10 (50)	6 (54)	
Race, n (%)			
White	11 (55)	6 (54)	
Black	7 (35)	5 (45)	
Asian	1 (5)	0 (0)	
SAP 24-2 MD, dB	-0.1 ± 1.4	0.6 ± 1.2	0.092
SAP 24-2 PSD, dB	1.6 ± 0.3	1.5 ± 0.2	0.481
*SD-OCT RNFL thickness, μm	81.7 ± 11.4	98.4 ± 10.5	< 0.001
mfSSVEP CCA ρ	0.291 ± 0.021	0.334 ± 0.028	< 0.001

*SD-OCT RNFL: Spectral domain optic coherence tomography retinal nerve fiber layer

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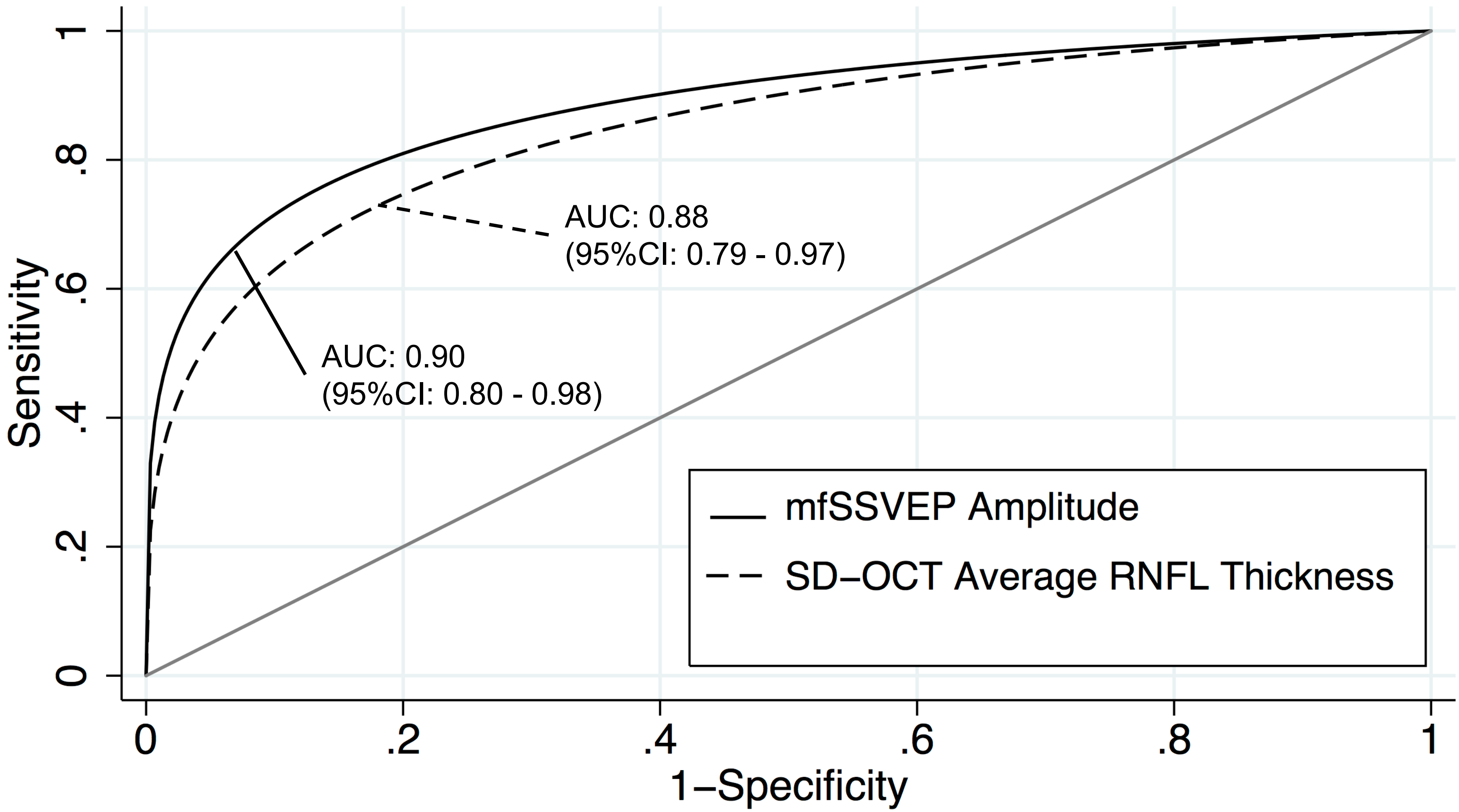
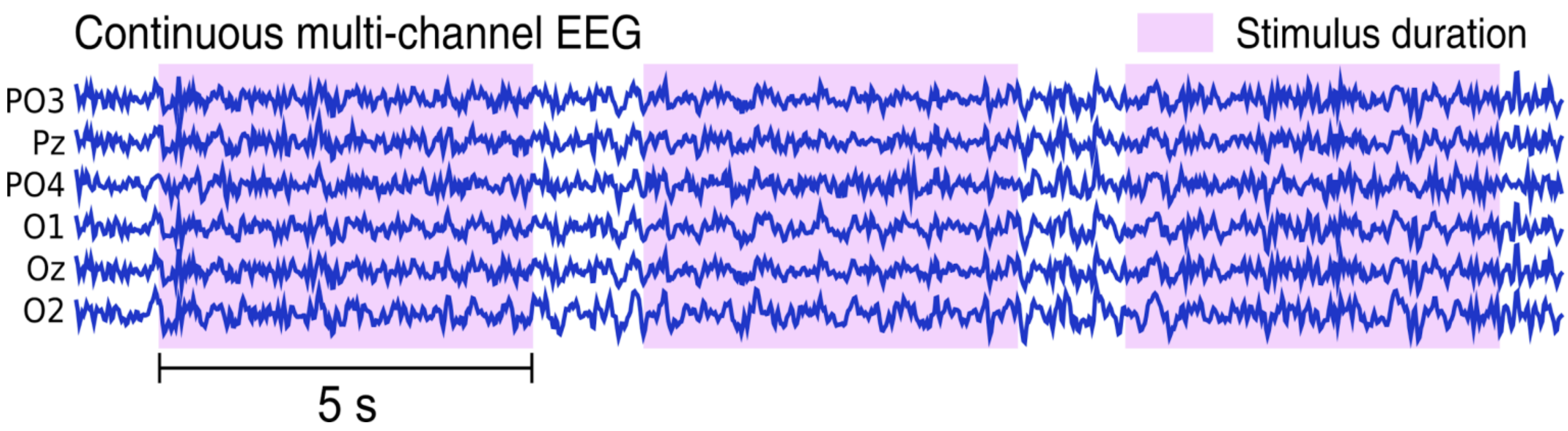
Diagnostic ability



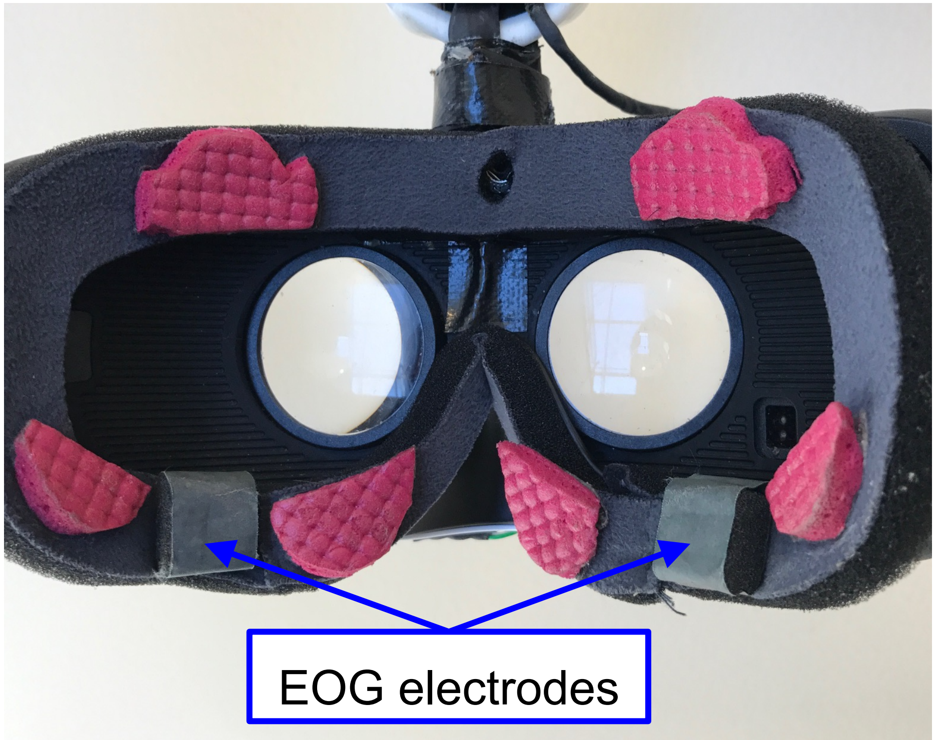
EEG preprocessing

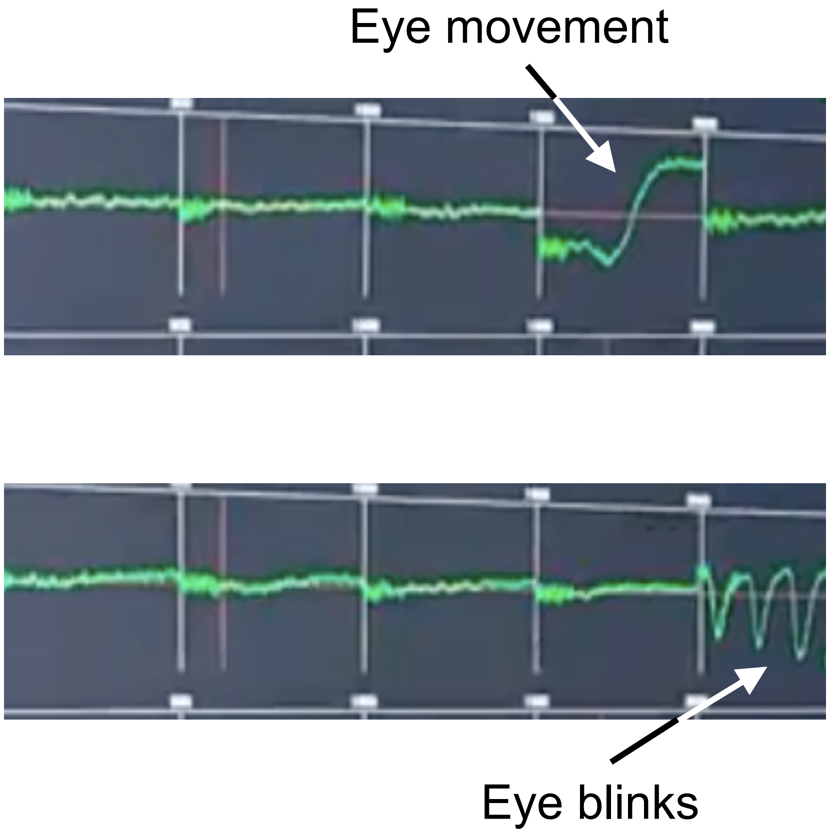
- 90 5-s data epochs were extracted from the recorded EEG data after band-pass filtering from 5 Hz to 25 Hz.



Monitoring fixation loss

- To remove data epochs with artifacts due to fixation losses, ones whose EOG amplitudes exceed a pre-defined threshold of ± 150 μV were removed.

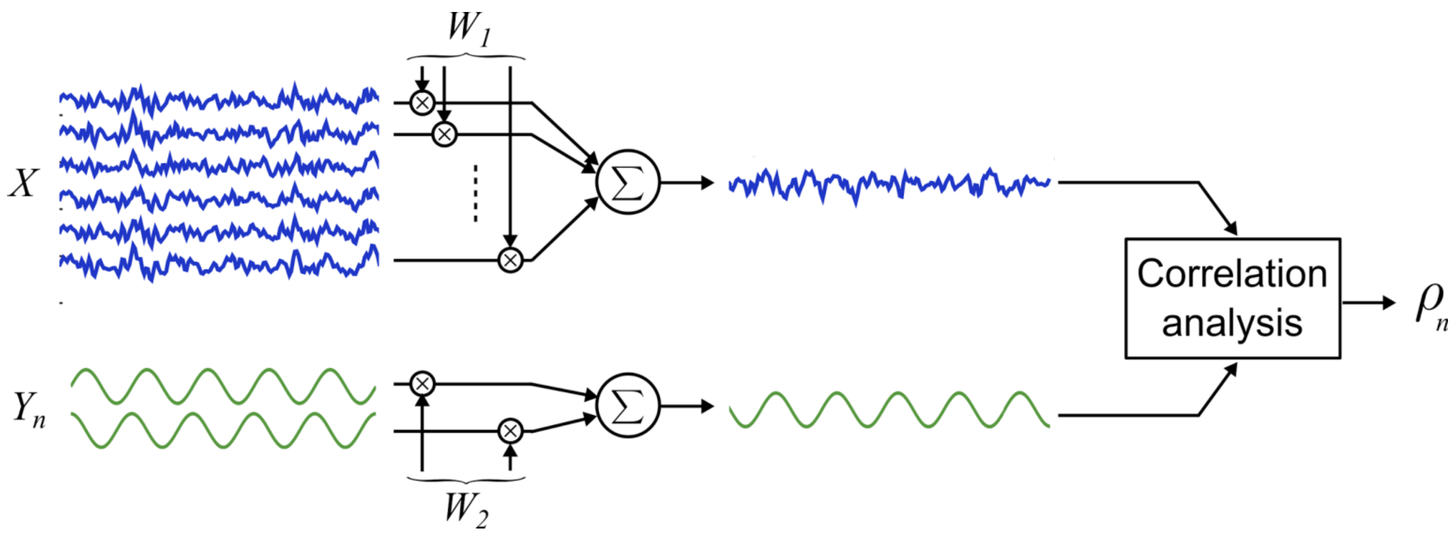




CCA-based measures[4]

- Canonical correlation analysis (CCA) measures underlying correlation between two sets of multidimensional variables.
- CCA finds a pair of linear coefficients that maximize the correlation between two variables projected onto the coefficients.
- Canonical correlation ρ_n for *n*-th sector can be calculated as follows:

$$\rho_n = \mathrm{CCA}(X, Y_n) = \mathrm{Corrcoef}(W_1{}^T X, W_2{}^T Y_n)$$



[4] Lin et al., *IEEE Trans. Biomed. Eng.* 2007

Data analysis

- A global metric ρ representing the overall CCA measures for each eye was calculated as:

$$\rho = \frac{1}{N}\sum_{n=1}^{N}\rho_n \qquad N = 20 \text{ [Sectors]}$$

- Receiver operating characteristic (ROC) curves were constructed to assess the diagnostic ability of the mfSSVEP CCA metric.
- A bootstrap resampling (n = 1000) was used to derive confidence intervals (CIs) taking into account correlated data from both eyes of same individual.

Popular EEG patterns / features

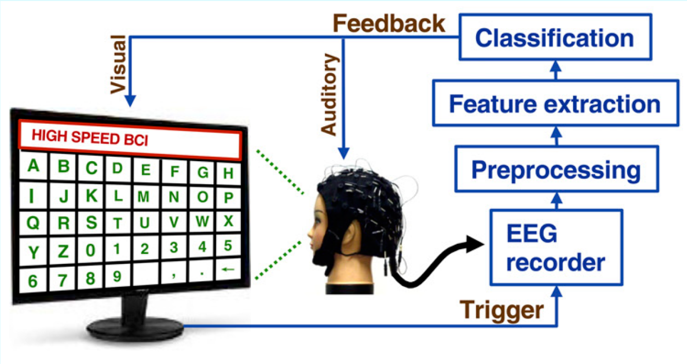
Motor imagery

Event-related potentials (ERPs)

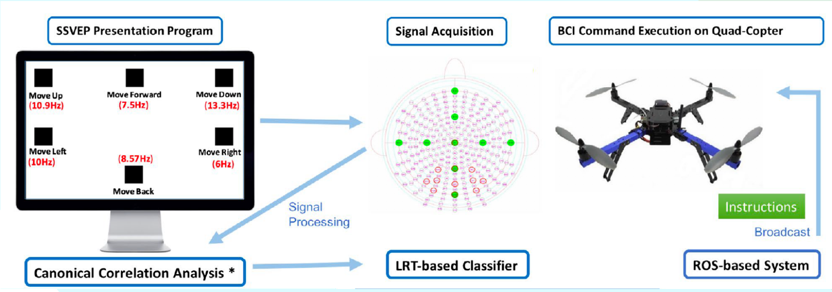
Visual evoked potentials (VEPs)

Applications of SSVEPs

Brain-computer interface (BCI)

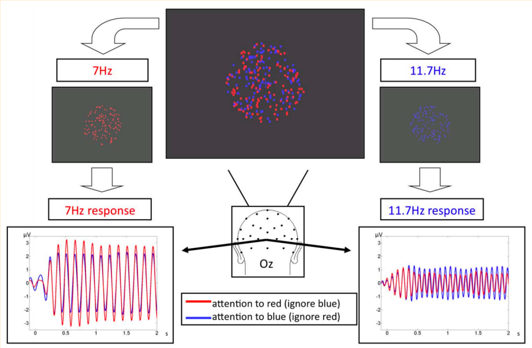


Text speller (Chen et al., 2015)

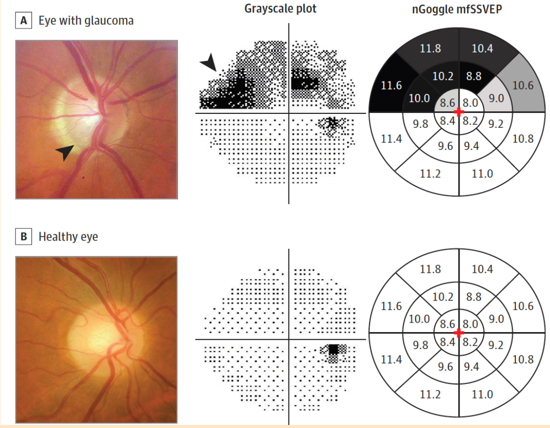


Controlling vehicle (Merino et al., 2017)

Visual neuroscience



Selective attention (Muller et al., 2006)



Assessment of visual impairment (Nakanishi et al., 2017)

Research topics in the field of SSVEP

- **Hardware**
  - Visual stimulation device (i.e., LED, CRT, or LED)
  - Electrode (e.g., wet, dry, non-contact, or…)
  - EEG amplifier system (e.g., wired, or wireless)
- **Software**
  - Visual stimulus design (e.g., frequency, #, color, pattern)
  - Noise / Artifact reduction (e.g., line noise, muscle activity)
  - Signal analysis (e.g., Machine/Deep learning)
- **Translational study**
  - Designing clinical applications
  - Testing BCI systems with patients

Research topics in the field of SSVEP

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