Fast Visual Target Identification for Low-Cost BCI Speller

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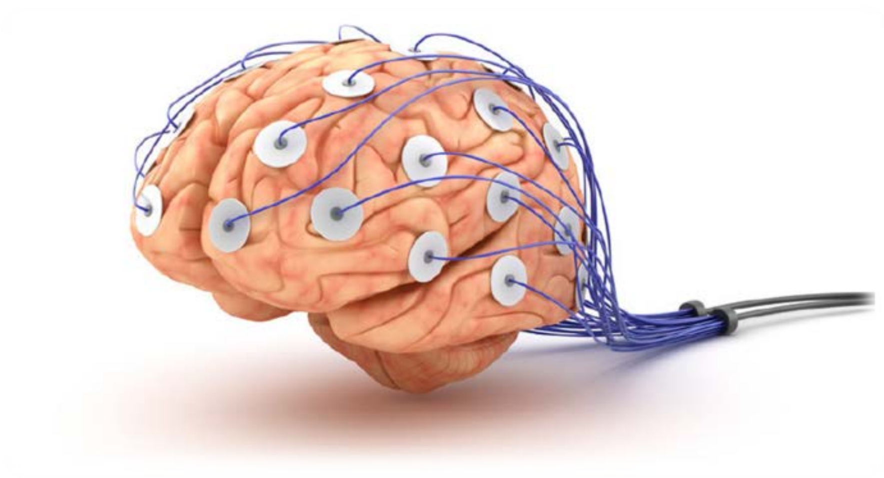
Outline

- What is the brain-computer interface?
- Research goal
- Previously developed wearable BCI device
- Proposed target identification algorithm
- Experimental results
- Further work – make our own hardware
- Conclusion

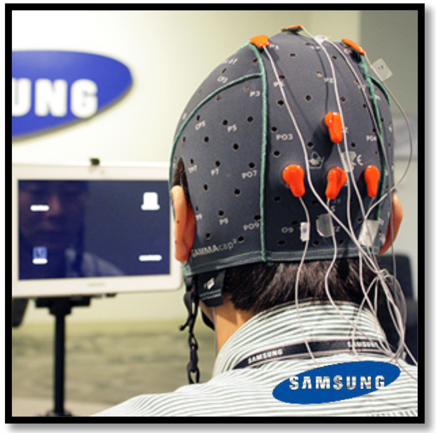


Brain-Computer Interface

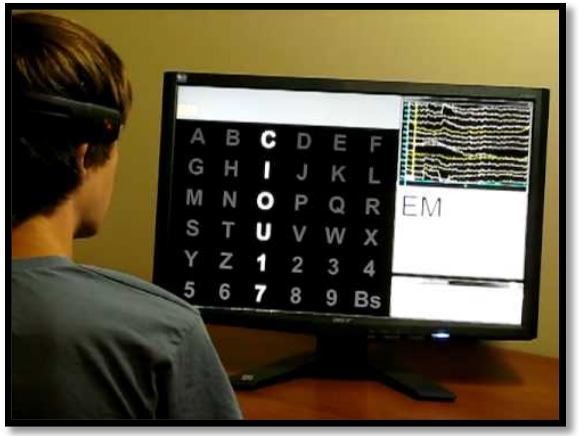
- Brain-Computer Interface (BCI) - emerging communication channel for humans

Jan Scheuermann, DARPA

Courtesy Georgia Tech BrainLAB



Samsung



Lyon Neuroscience Research Center, 2012

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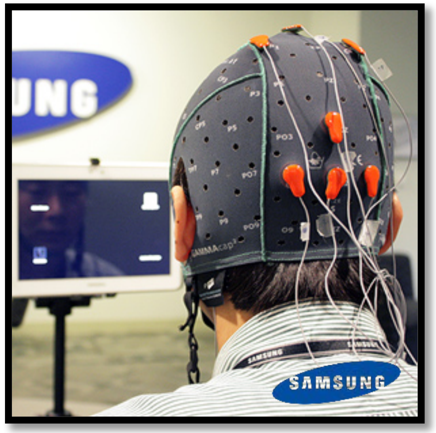

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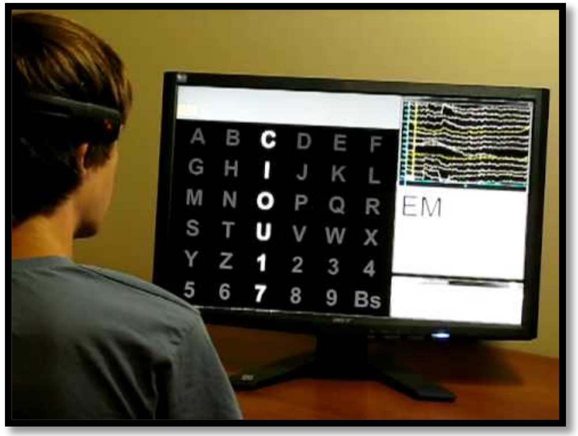

Lyon Neuroscience Research Center, 2012

Invasive

Non-invasive

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Samsung

Lyon Neuroscience Research Center, 2012

BCI Speller

BRAIN-COMPUTER INTERFACE

- Brain-Computer Interface (BCI) - emerging communication channel for humans

Graffiti artist, Tempt

Physicist, Hawking

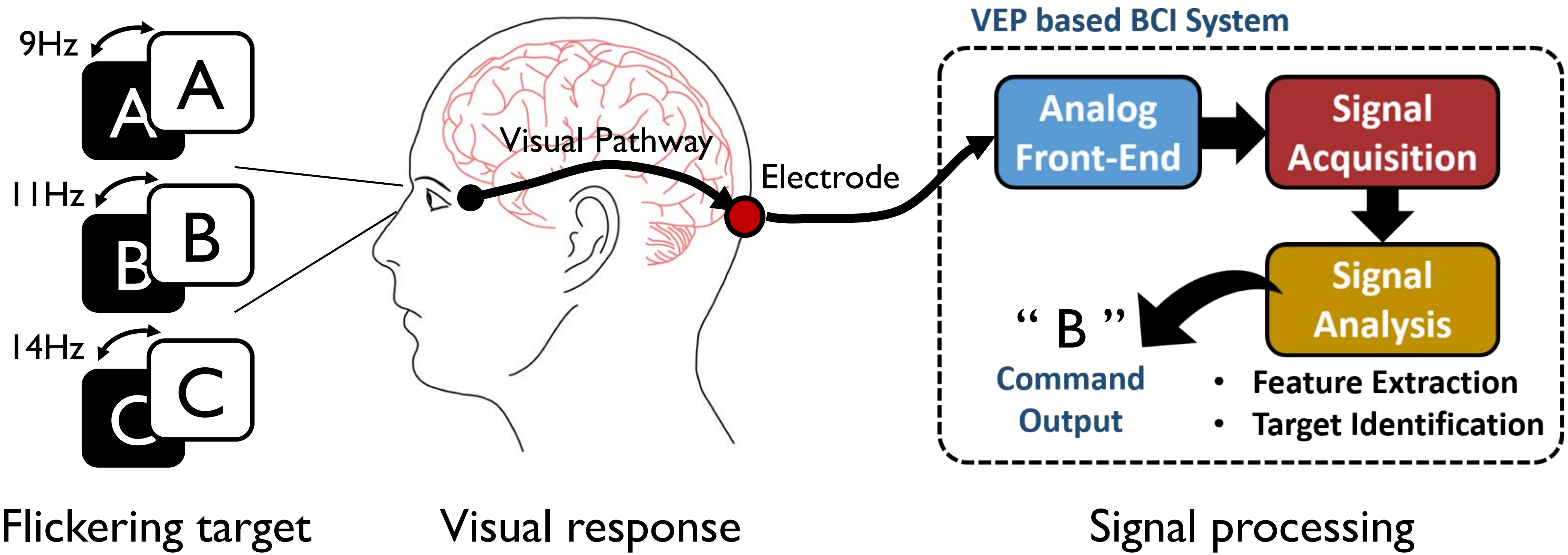
Lyon Neuroscience Research Center

BCI Speller

- Can help patients with paralysis communicate with other people (stroke, spinal cord injury, …)
- Using non-invasive electroencephalogram (EEG) → non-invasiveness, simple operation

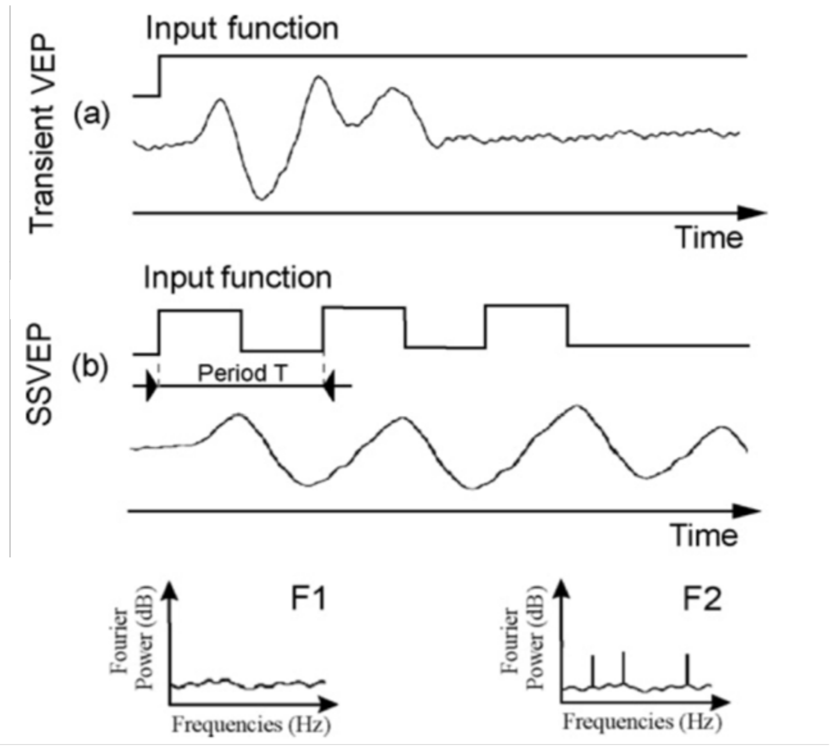
STEADY-STATE VISUAL EVOKED POTENTIAL

- Information transfer through visual evoked potentials (VEPs)
  - SSVEP: EEG response to flickering visual stimulation at a specific frequency

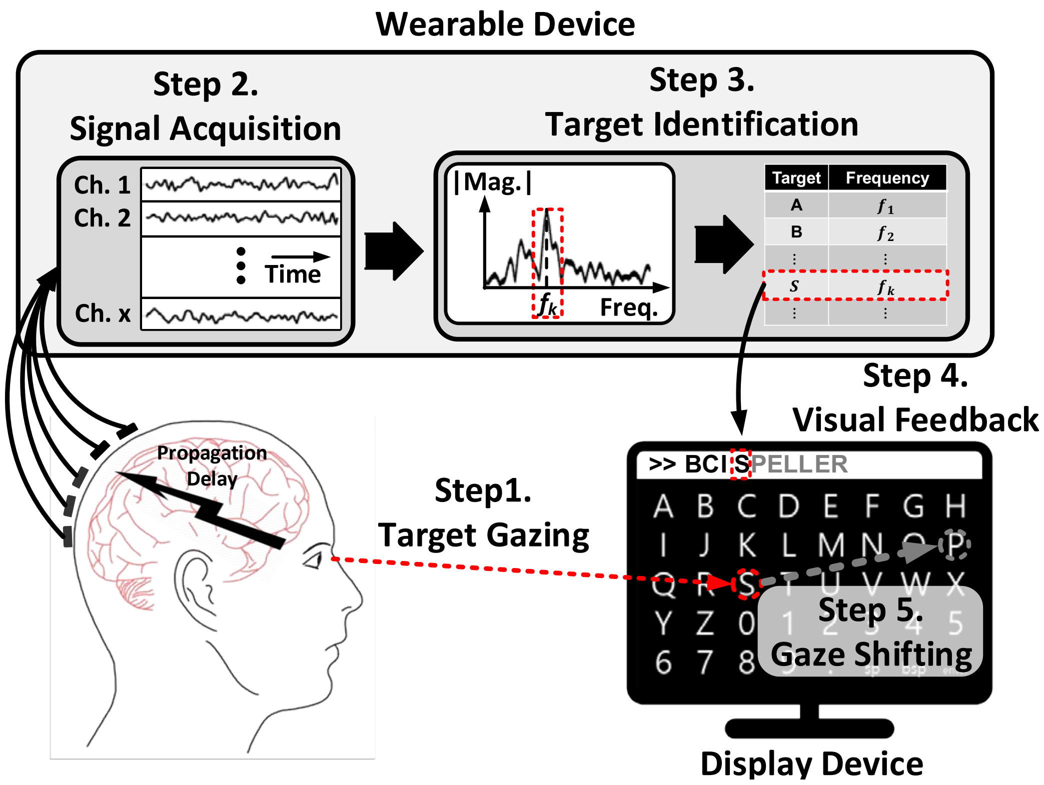


VISUAL TARGET IDENTIFICATION IN BCI SPELLER

- Information transfer through visual evoked potentials (VEPs)
  - SSVEP: EEG response to flickering visual stimulation at a specific frequency



Francois-Benoit Vialatte, 2009



RESEARCH GOAL

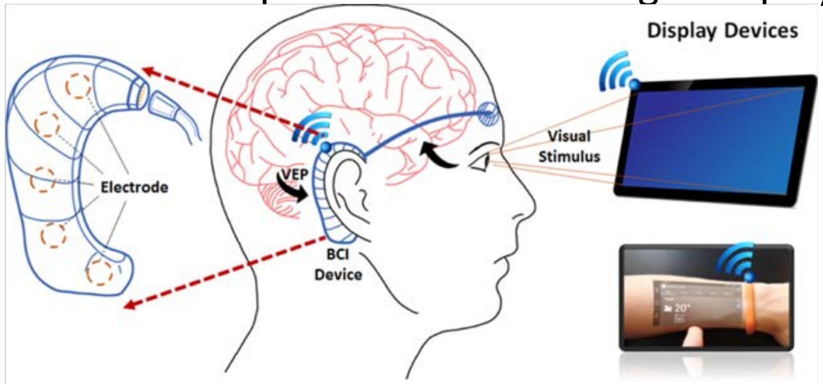
Previous BCI speller system

- Attaching many electrodes on the head
  - Discomfort to wear
  - Long preparation/setup time
- EEG signal processing in PC
  - Need powerful computing resource

Previous BCI speller system

Goal : Wearable BCI speller system

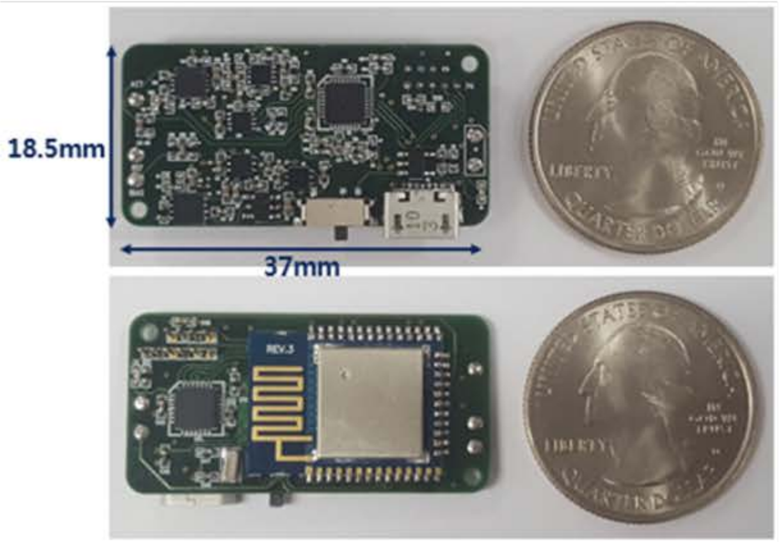
- BCI device with better wearability
  - Support on-device EEG processing
    - Based on Low-power MCU platform
  - Display device with Bluetooth
    - Target character display : visual stimulus
    - On-line speller : Identified target display

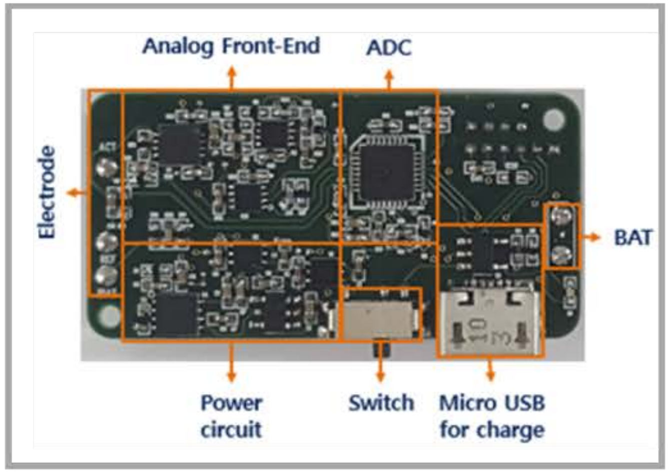


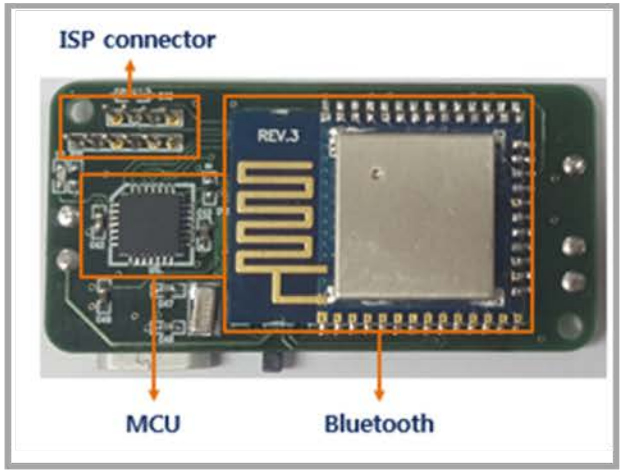
Wearable BCI speller system

WEARABLE BCI DEVICE PROTOTYPE

- Behind-the-ear type device
  - Single-channel EEG + Bluetooth 4.0
  - Target identification software on host PC (EEG data transfer through Bluetooth)
  - 24-bit resolution ADC chip (for performance evaluation)







Co-work with Seoul National University (SNU)

Wearable BCI Device Prototype

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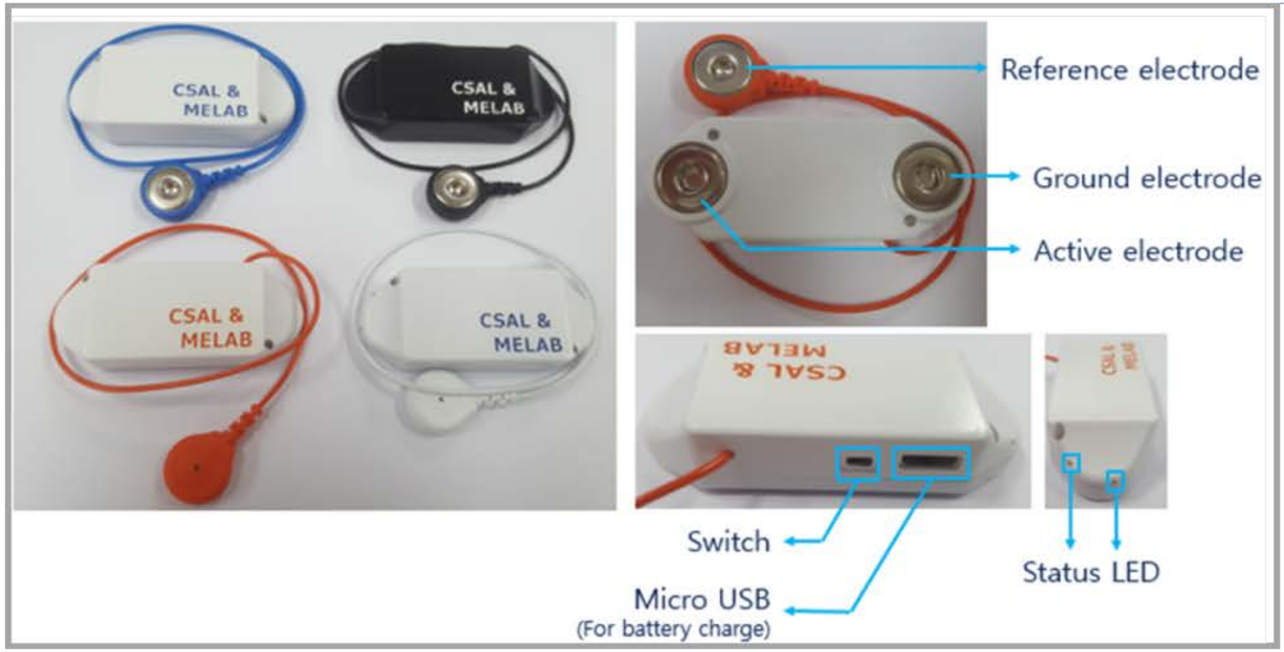


IRB (Institutional Review Board) approved

COMPARISON TO COMMERCIAL DEVICES

- Small size & low power
  - Comfortable
  - Long battery life
- High performance
  - Low noise
  - High resolution
- But…
  - Requires powerful computing PC

	This Work	Neuroscan	EMOTIV EPOC	Neurosync
				
Dimension (mm)	54 x 20 x 10	-	-	63 x 40 x 25
Weight (g)	14.3	-	104.3	43
Number of Ch.	1	64-512	14	1
Sampling rate (SPS)	250 / 500	Up to 20,000	127	N/A
ADC reference (V)	±2.42	Adjustable	N/A	
Amplification (V/V)	59,400	Adjustable	N/A	
Dynamic range	±40.74	Adjustable	8,400	
Noise level (μVrms)	0.11	0.5	about 1	
Resolution	24bit / 48.4nV	24bit / 3nV	14bit / 0.51μV	
Bandwidth (Hz)	1-35	DC-3,500	0.2-45	
Communication	Bluetooth 4.0	USB	2.4GHz	
Power	Li-polymer	Wall power	Li-polymer	AAA battery
Power consumption	19 hour		12 hour	N/A

Improvement Direction of Prototype Device

- **Not Enough SNR: Poor SSVEP quality at behind-the-ear position**

- **Not Enough Computing Power: Requires external computing device**

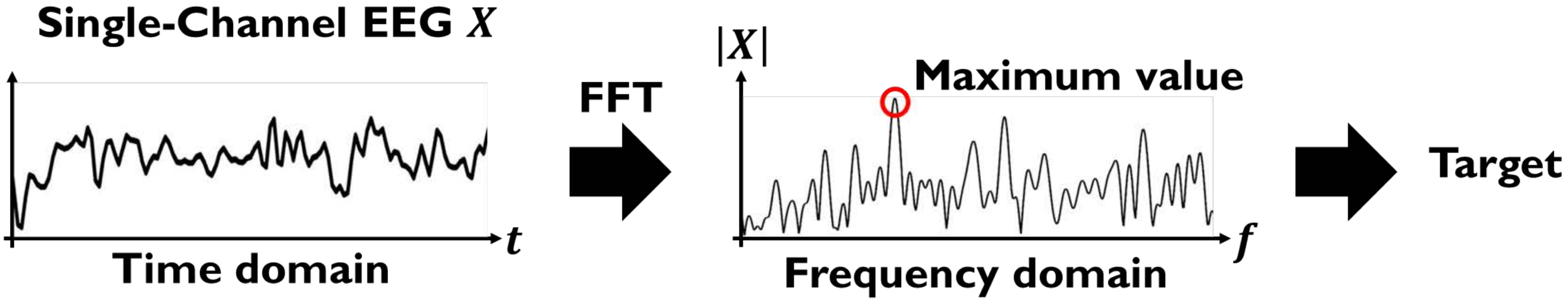
- **Not Enough Communication Speed**

Improvement Direction of Prototype Device

- **Not Enough SNR: Poor SSVEP quality at behind-the-ear position**
  - Move the electrode to back of the head (occipital region, Oz)
- **Not Enough Computing Power: Requires external computing device**
  - Propose the target identification algorithm for low-cost MCU and small memory
  - Maintain the BCI speller performance with negligible accuracy loss
- **Not Enough Communication Speed**
  - Reduce the signal processing time especially the timing dependent procedures

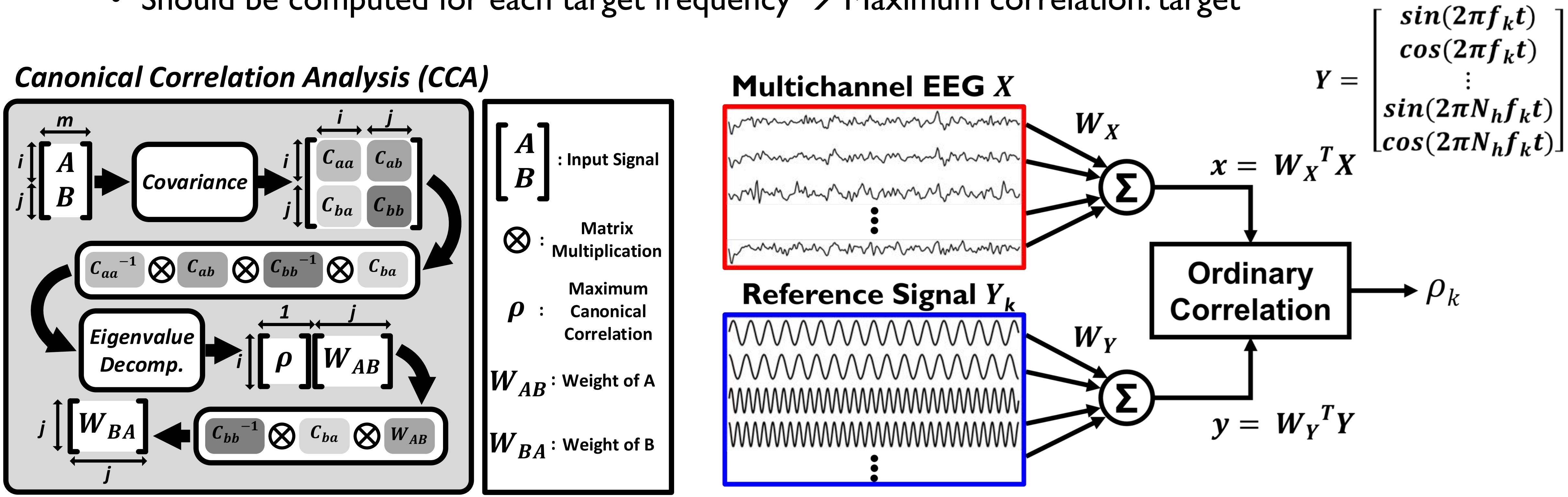
Target Identification Algorithms

- PSDA (Power Spectral Density Analysis)
  - For single-channel SSVEP target identification
  - Simple operation: FFT & find maximum index
  - Weak performance for low SNR (signal-to-noise) SSVEP signal



Target Identification Algorithms

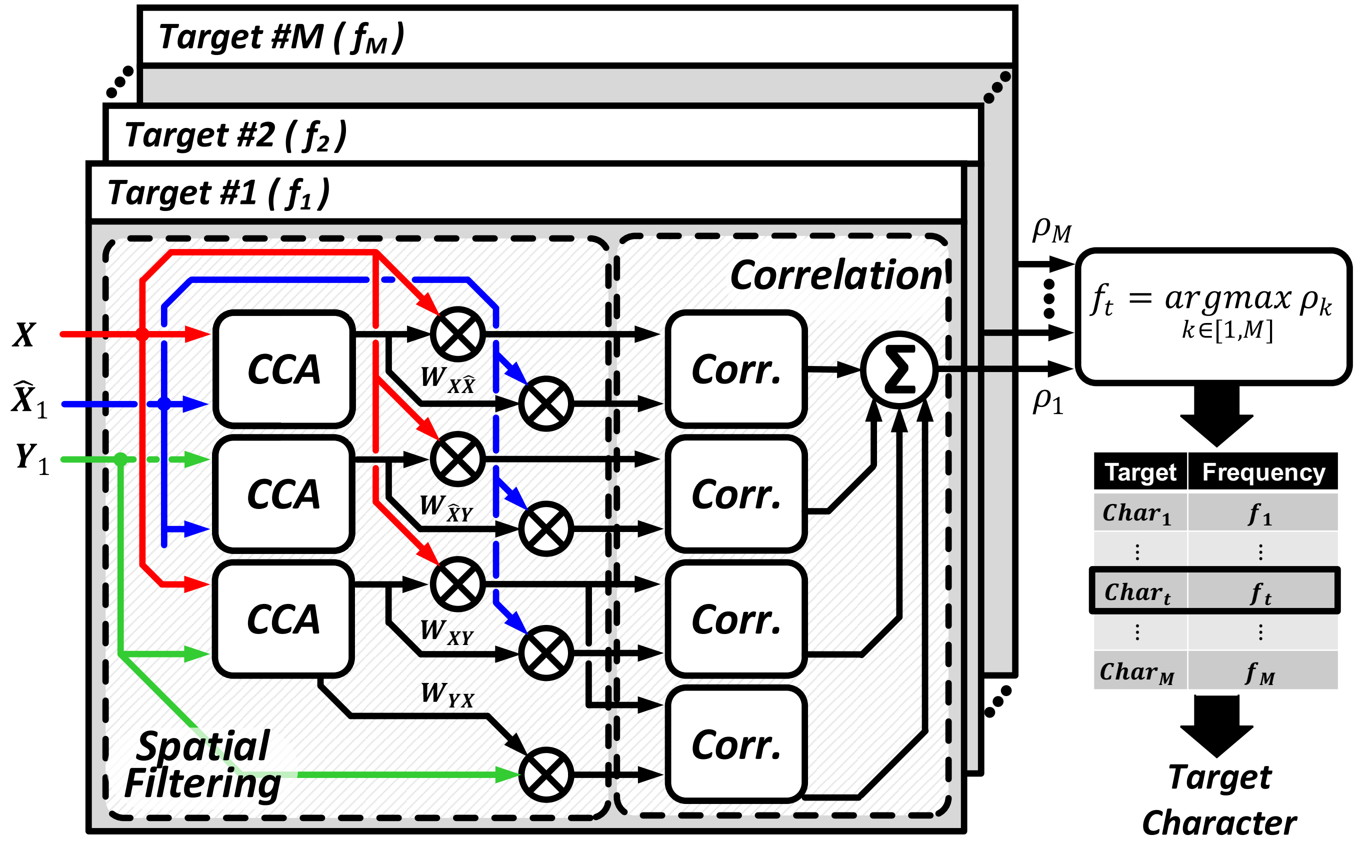
- Standard-CCA (Canonical Correlation Analysis)*
  - Correlation between EEG signal ***X*** and reference sinusoidal signal ***Y*** for each frequency
  - Should be computed for each target frequency → Maximum correlation: target



* Z. Lin et al, "Frequency Recognition Based on Canonical Correlation Analysis for SSVEP-Based BCIs", IEEE TBME, 2007

Target Identification Algorithms

- Combination-CCA (Comb-CCA)*



- User-specific target identification using training data → more accurate!
- Uses three datasets
  - X: Input SSVEP signal set
  - $\hat{X}$: Training signal set (average of SSVEP)
  - Y: Reference sinusoidal signal set
- 3 CCA calculations & 4 correlations → huge computational complexity

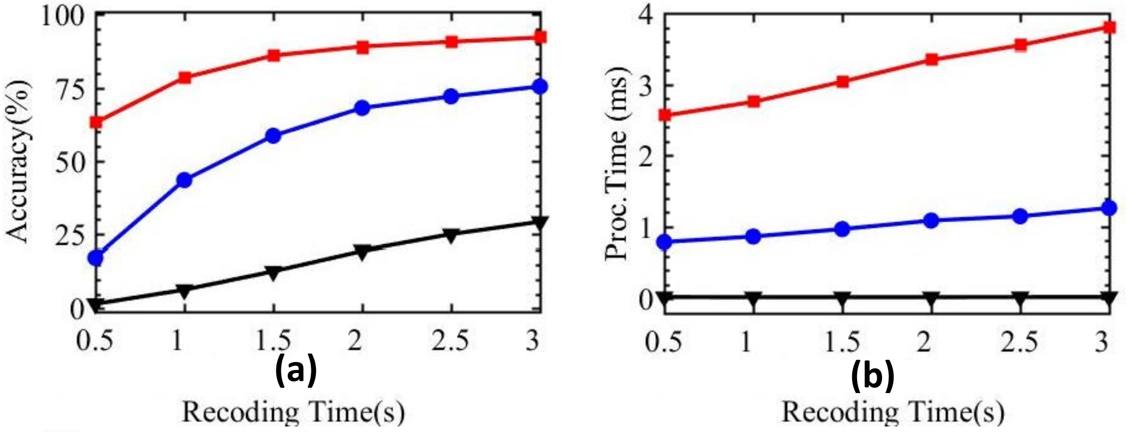
* M. Nakanishi et al, "A Comparison Study of Canonical Correlation Analysis Based Methods for Detecting Steady-State Visual Evoked Potentials", PLoS ONE, 2015

Target Identification Comparison

- Performance evaluation in terms of accuracy, processing time, and ITR (information transfer rate)

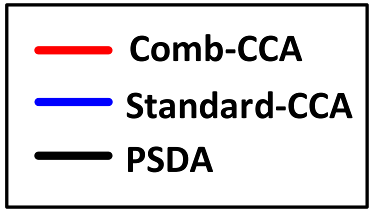
Algorithm	Performance	Complexity
Comb-CCA	**High**	**High**
Standard-CCA	**Medium**	**Medium**
PSDA	**Low**	**Low**

- Comb-CCA was chosen for the baseline algorithm in this research



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

- ***P***: classification accuracy
- ***T***: average time for selection
- ***N_f***: number of targets



Performance comparison of target identification algorithms
(a) Accuracy, (b) Processing time (in PC), (c) ITR (Information Transfer Rate)

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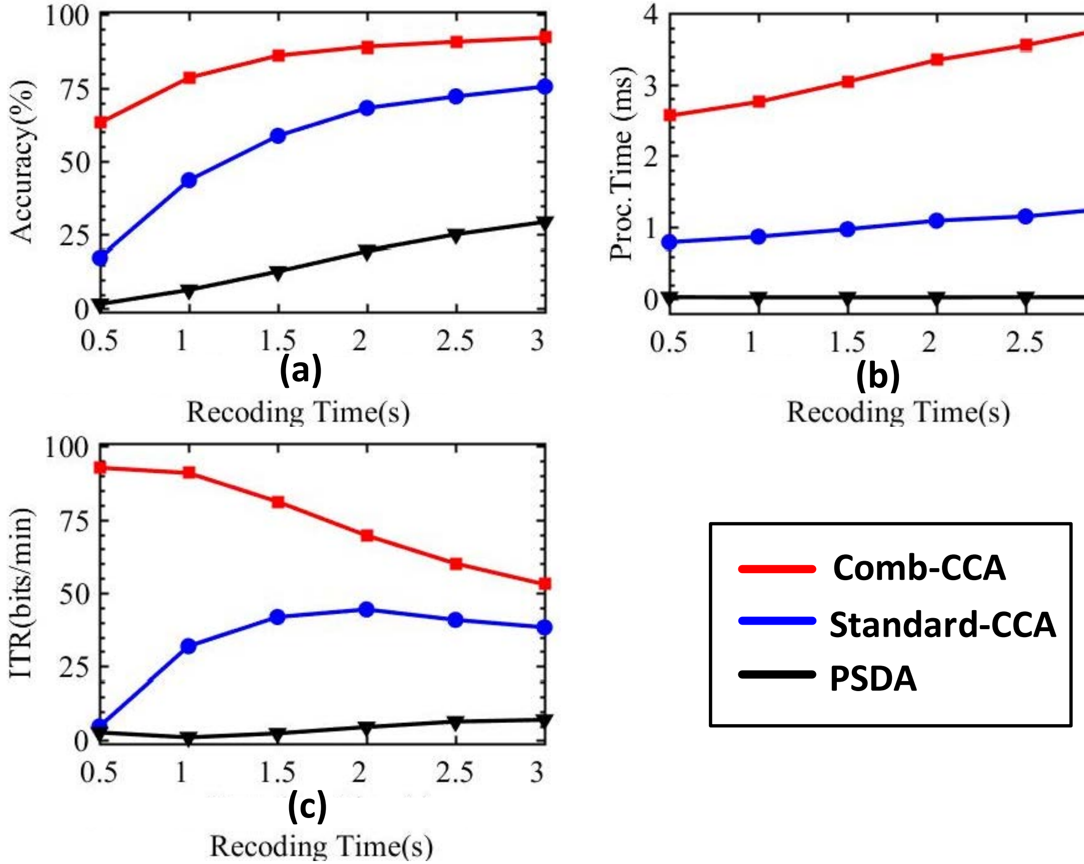

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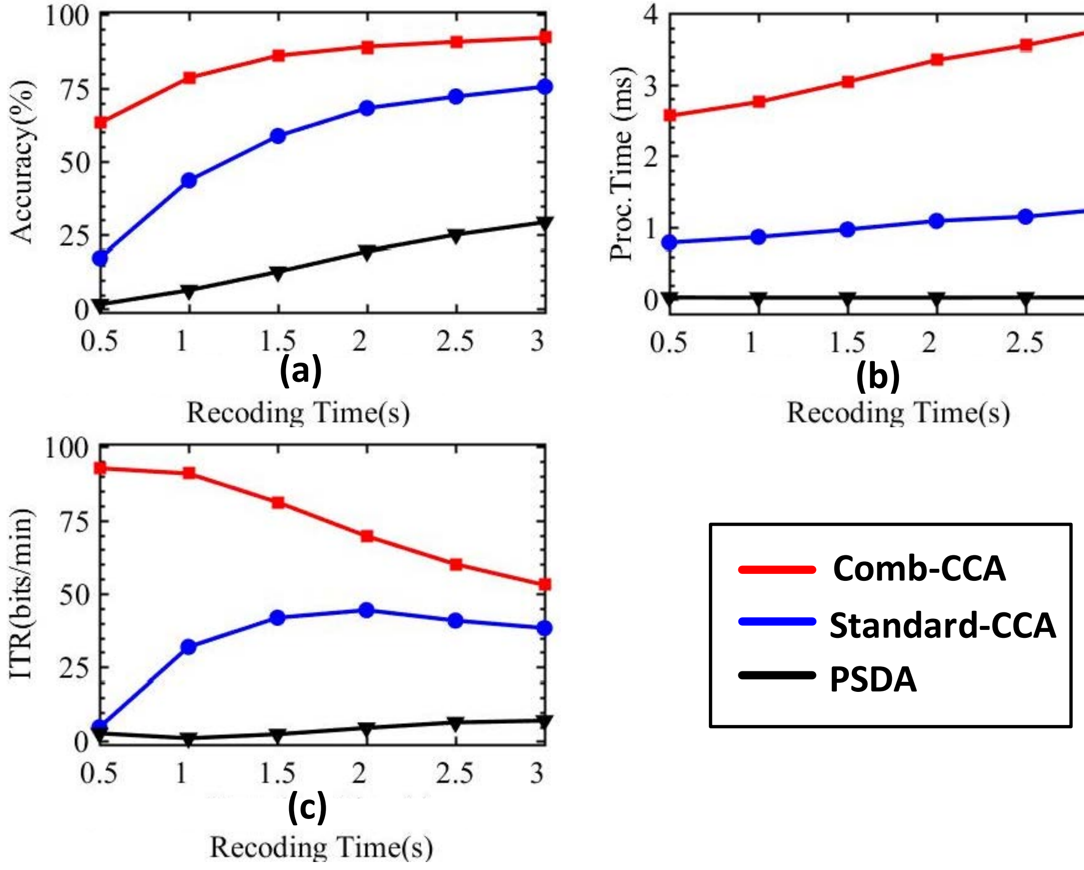
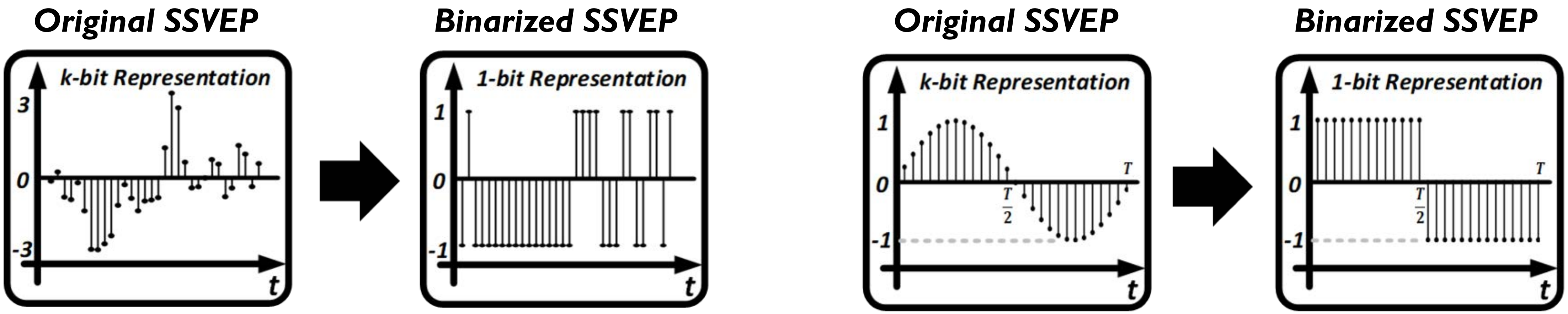


Performance comparison of target identification algorithms
(a) Accuracy, (b) Processing time (in PC), (c) ITR (Information Transfer Rate)

PROPOSED ALGORITHM: CCA-LITE

- **Optimization method #1: Signal Binarization**
  - Comb-CCA with multi-bit EEG & reference signal → High computational complexity / memory
  - Comb-CCA with signal binarization → Low computational complexity w/ negligible accuracy loss
    Low memory requirement



(a) (b)

Proposed signal binarization concept for (a) EEG signal, (b) Reference sinusoidal signal

Proposed Algorithm: CCA-Lite

- **Optimization method #2: *On-the-fly* Covariance**
  - $Cov(\boldsymbol{X}, \boldsymbol{Y}) = E[(\boldsymbol{X} - E[\boldsymbol{X}])(\boldsymbol{Y} - E[\boldsymbol{Y}])] = E[\boldsymbol{XY}] - E[\boldsymbol{X}]E[\boldsymbol{Y}]$

PROPOSED ALGORITHM: CCA-LITE

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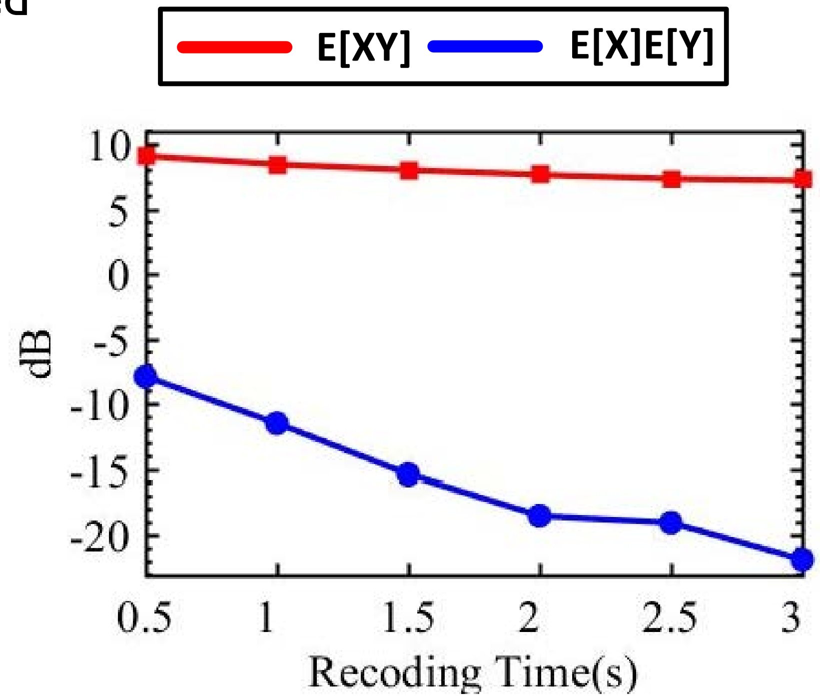
  - If $E[\boldsymbol{XY}] \gg E[\boldsymbol{X}]E[\boldsymbol{Y}]$ then $E[\boldsymbol{X}]E[\boldsymbol{Y}]$ can be ignored
    - In our application, $E[\boldsymbol{XY}]$ more bigger than $E[\boldsymbol{X}]E[\boldsymbol{Y}]$



Comparison of E[XY] and E[X]E[Y]

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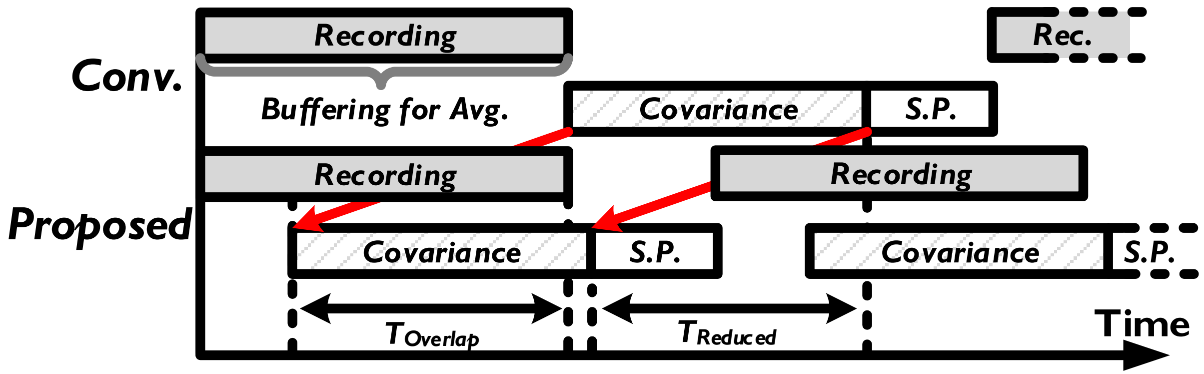
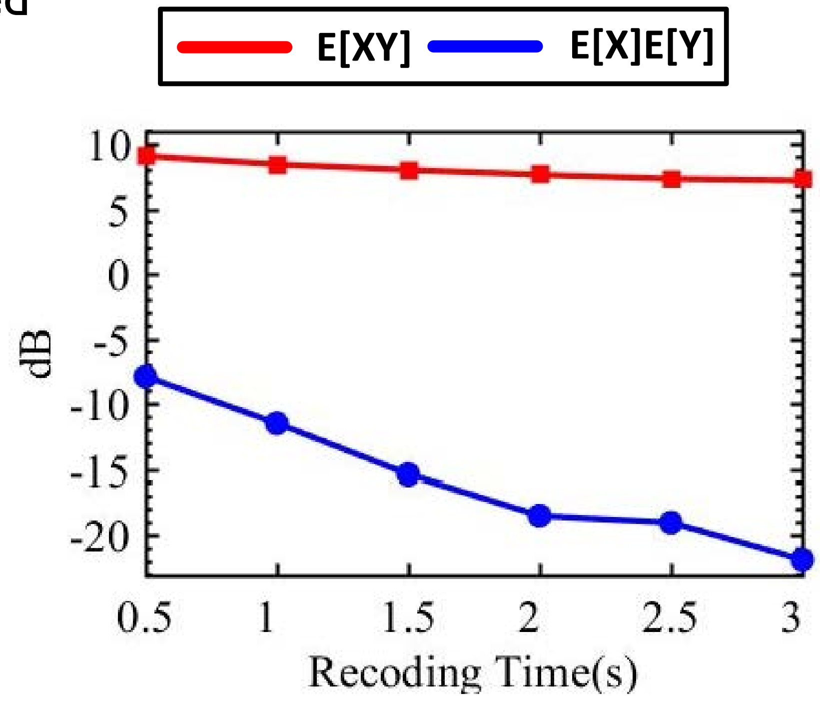
    - In our application, $E[\boldsymbol{XY}]$ more bigger than $E[\boldsymbol{X}]E[\boldsymbol{Y}]$
  - Covariance matrix calculation can be performed simultaneously with SSVEP recording



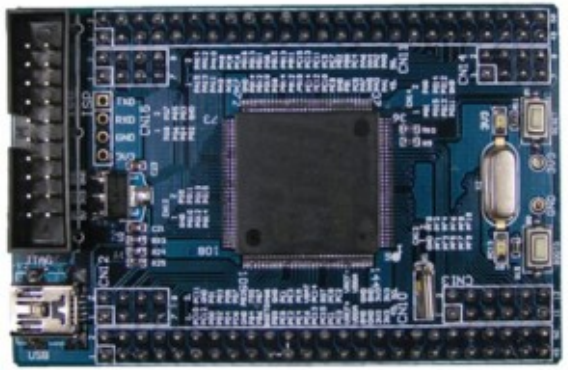
Advantage from *On-the-fly* Covariance Calculation



Comparison of E[XY] and E[X]E[Y]

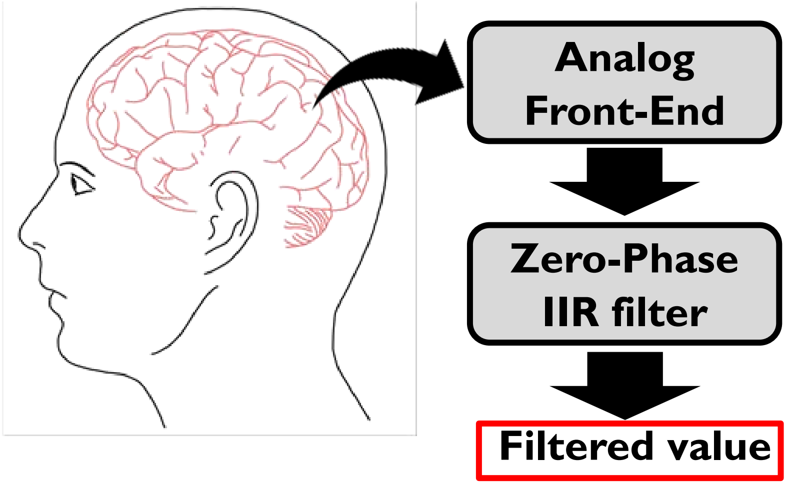
EXPERIMENTAL ENVIRONMENTS

- Low-power MCU platform
  - STM32F103ZET6 ARM MCU
    - ARM Cortex-M3 (Operating Frequency : 72MHz)
    - 512KB flash memory, 64KB SRAM



STM32F103ZET6 board

- Dataset Description *
  - EEG acquisition using *Biosemi's ActiveTwo*
  - ADC : 24-bit resolution
  - Sampling Frequency : 256Hz
  - Number of channel : 8 channels (We used Oz)
  - Recording Time : 4s
  - # of Target, # of subjects : 12 targets, 10 subjects



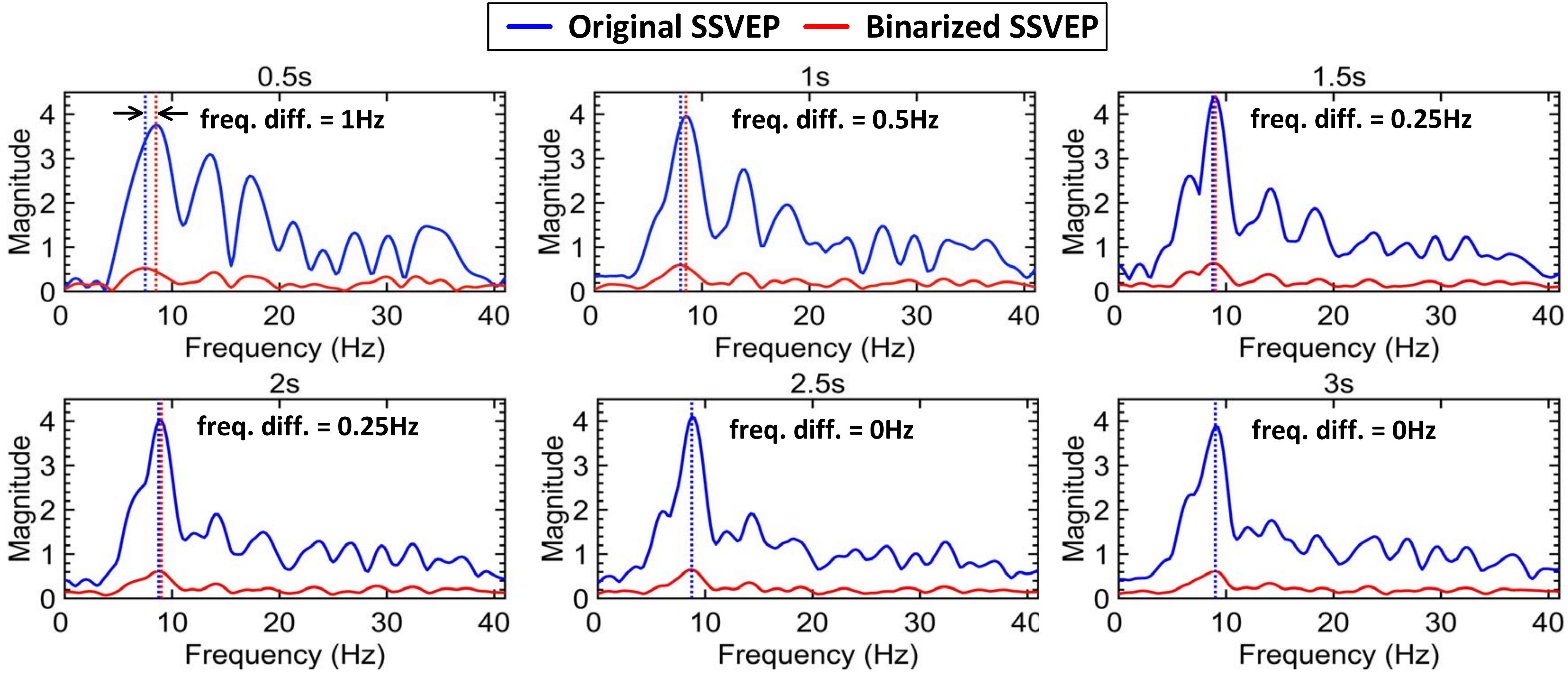
Pre-processing before writing the data file

* M. Nakanishi et al, "A Comparison Study of Canonical Correlation Analysis Based Methods for Detecting State-State Visual Evoked Potentials", PLoS ONE, 2015

EXPERIMENTAL RESULTS

- Subject #4
- Target: 9.25Hz

- Power spectrum of training signal according to the SSVEP recording length



Good
Moderate
Bad

Experimental Results

- Subject #4
- Target: 9.25Hz

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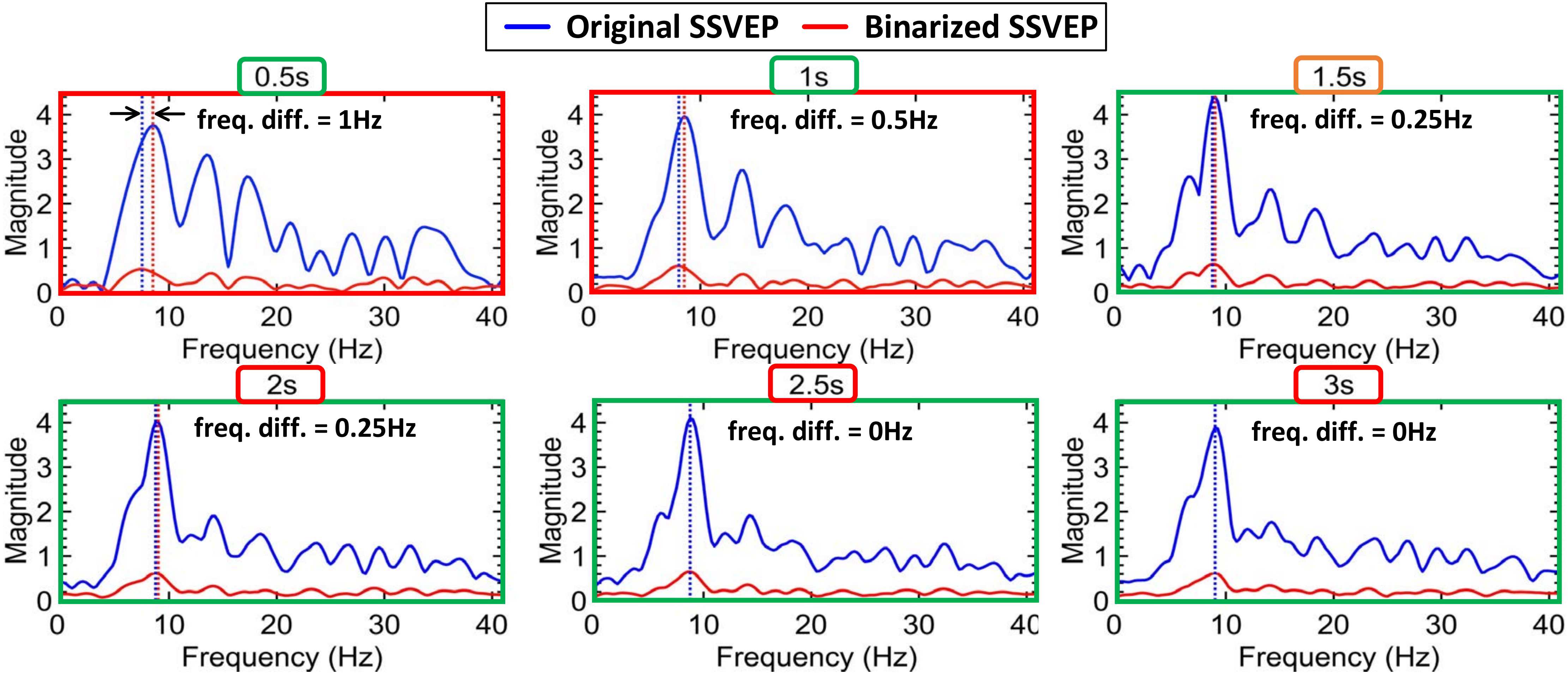
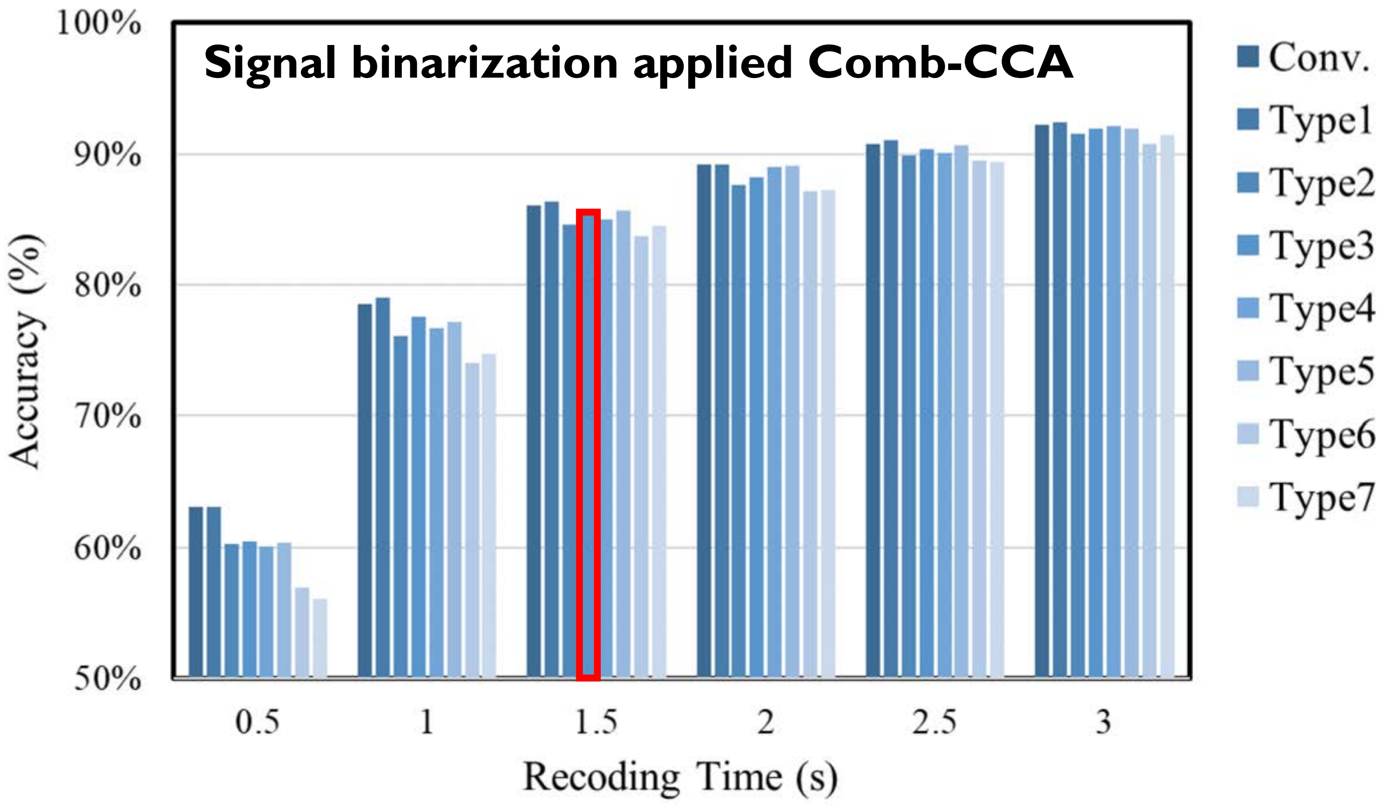


EXPERIMENTAL RESULTS

- Accuracy performance according to the combination of binarization application



Type3: High accuracy with small memory requirement

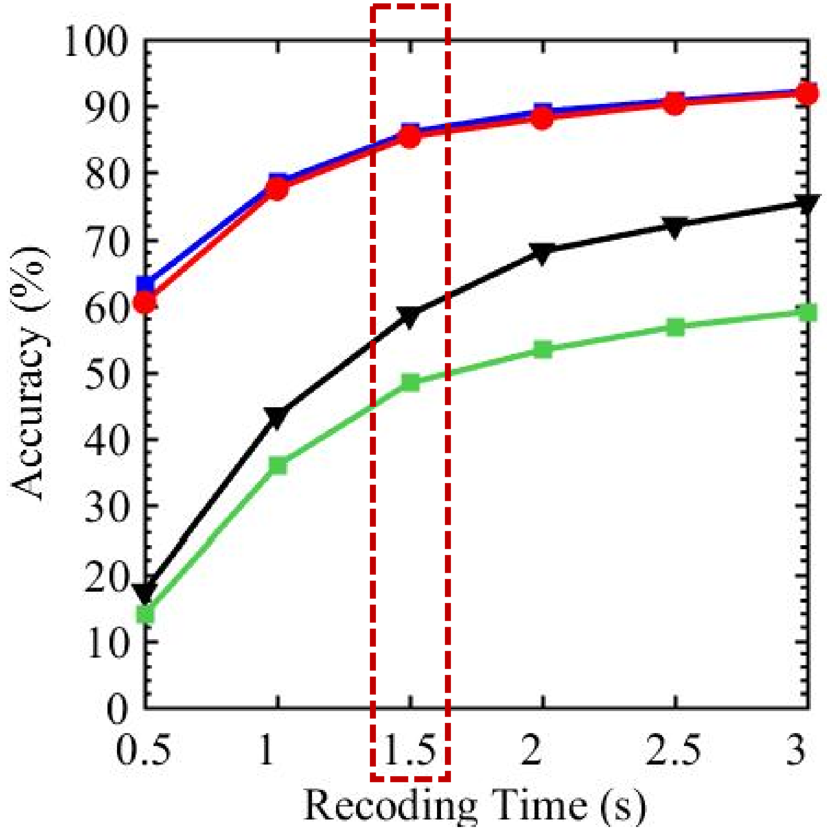
-- Training & Reference : pre-stored data

Type	Measured EEG	Training EEG	Reference Sinusoidal
Conv.	**X**	**X**	**X**
Type1	X	X	O
Type2	X	O	X
Type3	X	O	O
Type4	O	X	X
Type5	O	X	O
Type6	O	O	X
Type7	O	O	O

O: Signal binarization was applied
X: Signal binarization was not applied

Experimental Results

- Accuracy performance for various target identification algorithms
  - **CCA-Lite** : Comb-CCA + Signal Binarization (for Train & Ref.) + *on-the-fly* Covariance



Accuracy at 1.5s

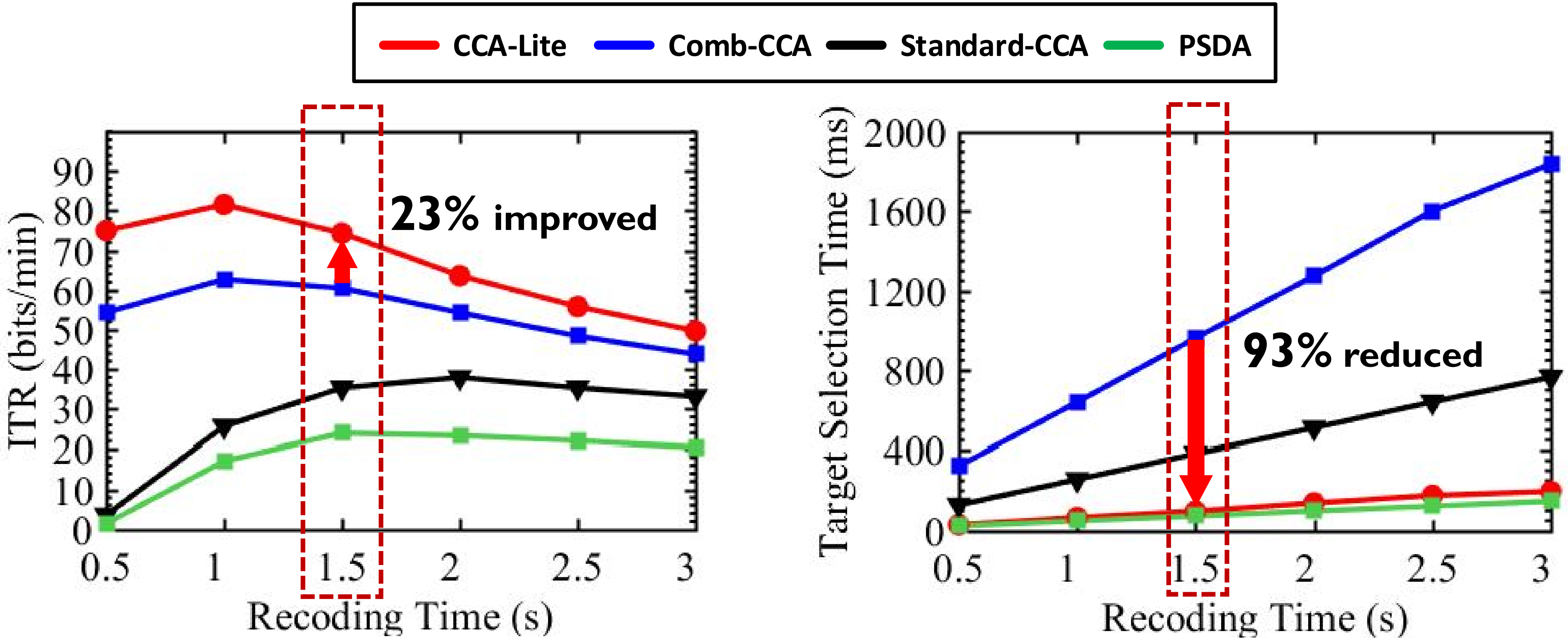
CCA-Lite	: 85.39%
Comb-CCA	: 86.06%
Standard-CCA	: 58.67%
PSDA	: 48.39%

Negligible Accuracy Loss

- CCA-Lite
- Comb-CCA
- Standard-CCA
- PSDA

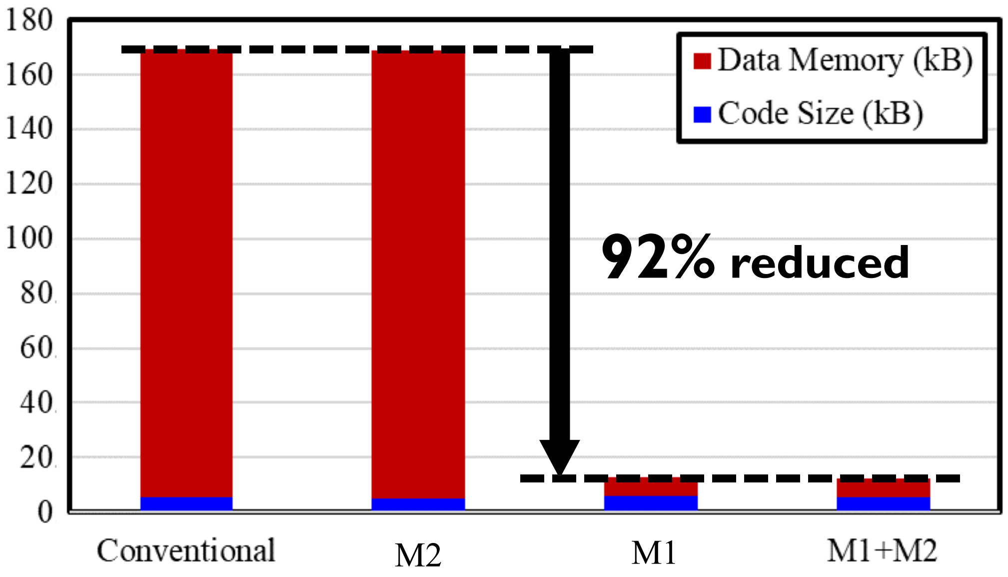
EXPERIMENTAL RESULTS

- Performance of target selection time & ITR (Information Transfer Rate)
  - Tested on Cortex-M3 based STM board (operating frequency: 72MHz)



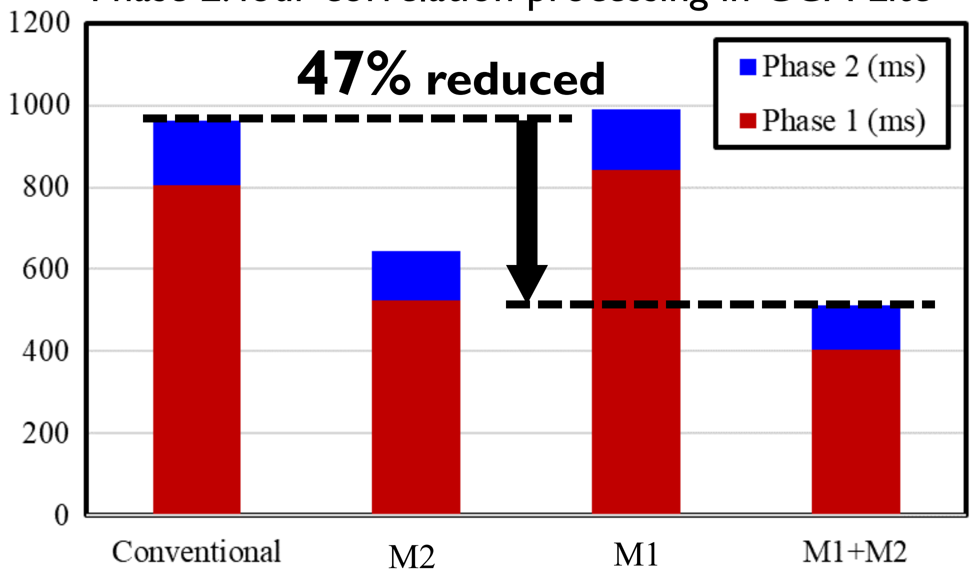
Experimental Results

- CCA-Lite software performance evaluation on Cortex-M3
  - **M1**: Signal binarization applied Comb-CCA / **M2**: *on-the-fly* covariance applied Comb-CCA
  - **M1+M2**: proposed CCA-Lite



Memory footprint

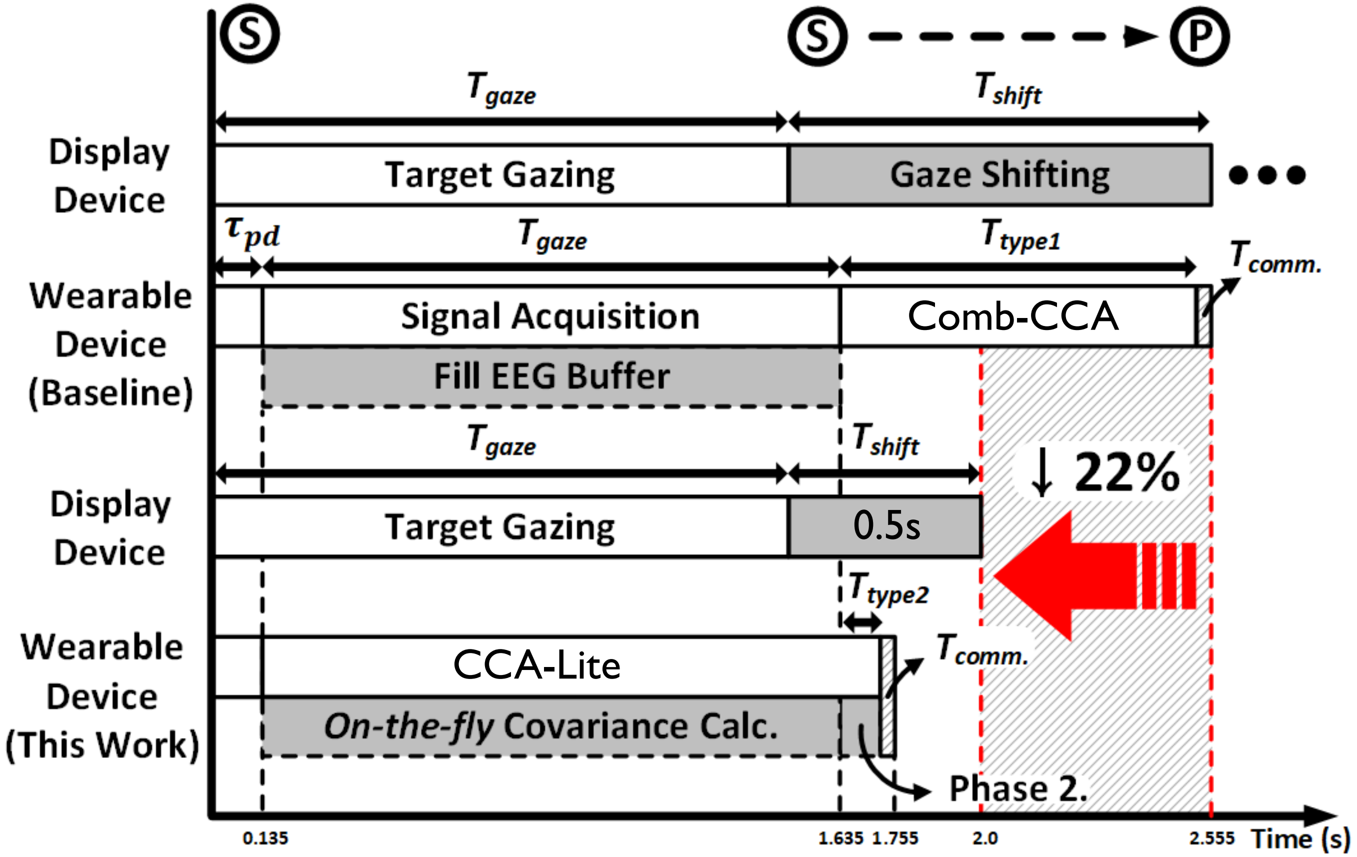
Phase 1: three CCA processing in CCA-Lite
Phase 2: four correlation processing in CCA-Lite



Pure signal processing time on Cortex-M3 for single target identification

EXPERIMENTAL RESULTS

- Overall BCI speller system performance in terms of communication speed

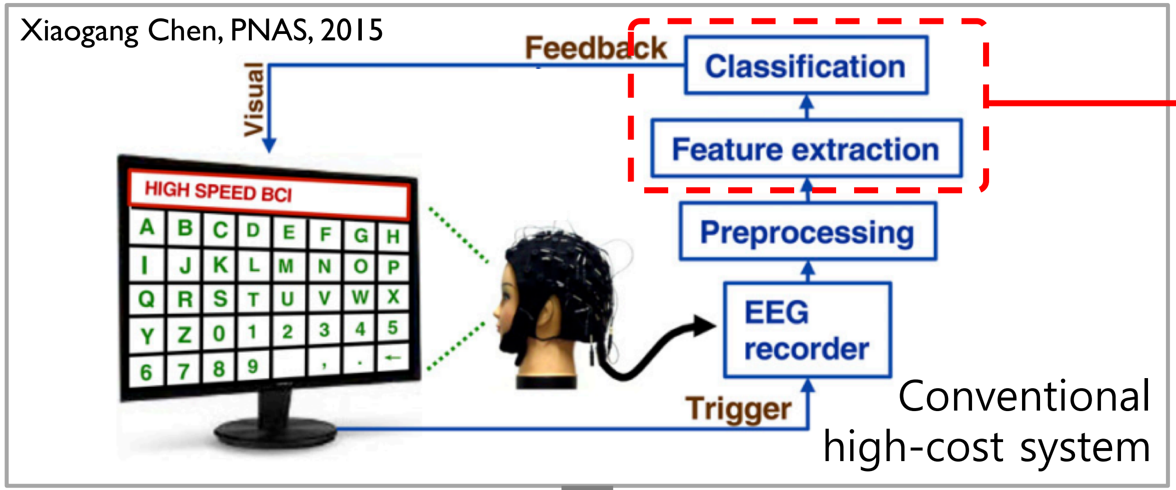


- Fixed target gazing time: 1.5s
- Minimum gaze shift time: 0.5s [1,2]
- Single target identification time
  - **22%** reduced !
  - Guaranteed gaze shift time 0.5s (signal processing will be done before the end of gaze shift time)

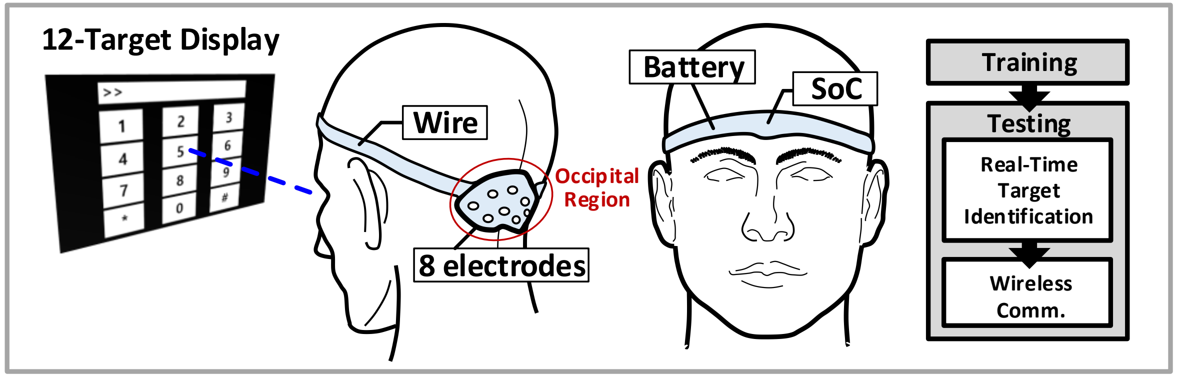
1) X. Chen et al, "High-speed spelling with a noninvasive brain-computer interface", PNAS, 2015
2) M. Nakanishi et al, "Enhancing Detection of SSVEPs for a High-Speed Brain Speller Using Task-Related Component Analysis", IEEE TBME, 2018

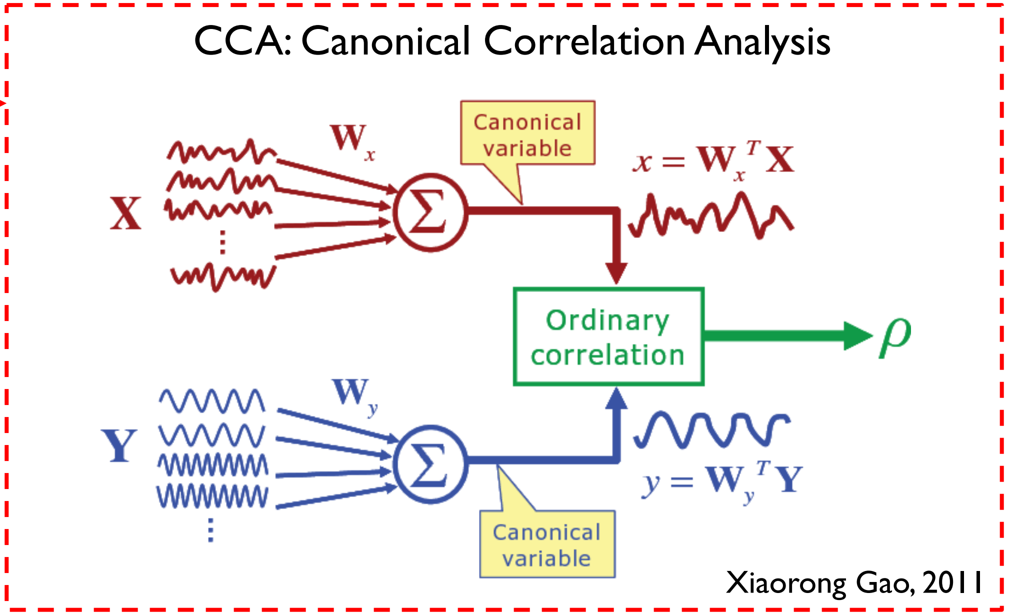
Reusable Matrix Arithmetic Architecture

- SSVEP-based Target Identification SoC with Highly Reusable 8x8 QRD



wearable system

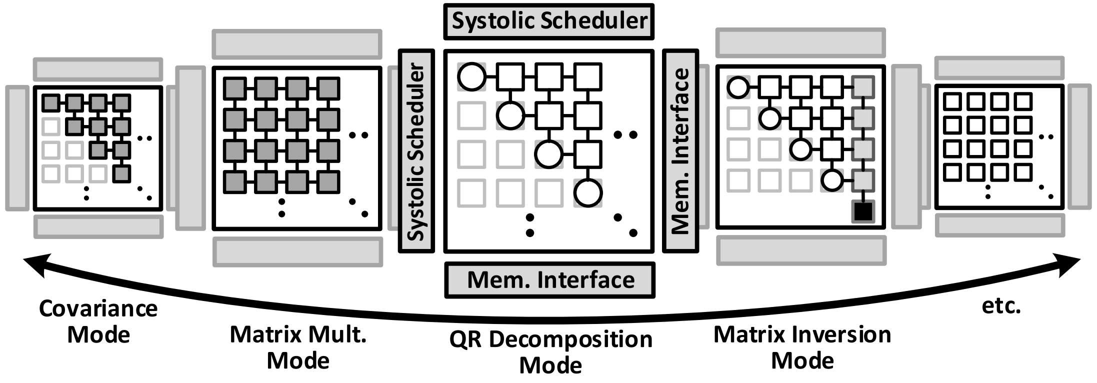


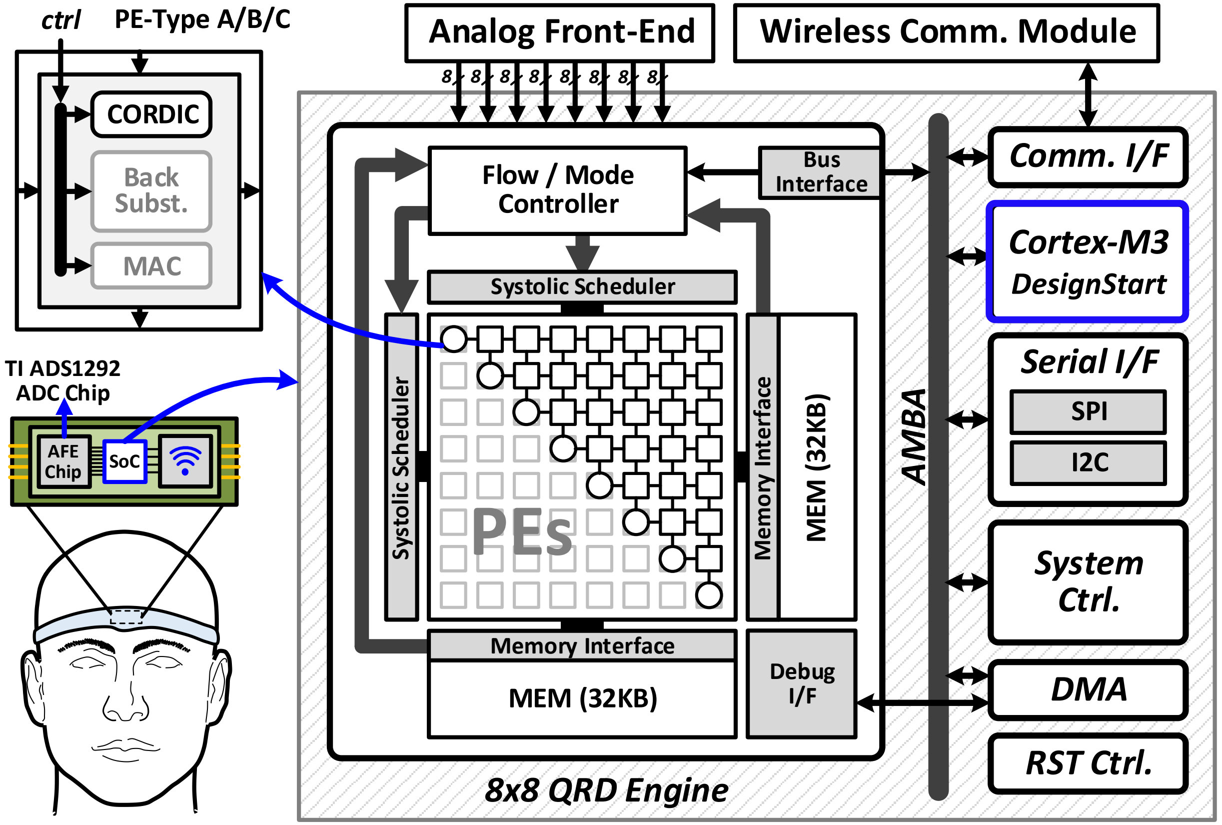


- CCA finds the weights **Wx, Wy** which gives the largest correlation between **X** and **Y** (target frequency identification)
- We use CCA-Lite consisting of three CCAs.
  - Requires QRD, Inverse, Covariance, Mult. …

Reusable Matrix Arithmetic Architecture

- SSVEP-based Target Identification SoC with Highly Reusable 8x8 QRD
  - Systolic architecture based QR decomposition engine





- Same hardware, different operations → high reusability (covariance, mult, QRD, inversion, …)
- "High throughput, reduced area & memory access, reduced power consumption" compared to same operations
- Target frequency identification on the low-cost edge devices.
- System implementation w/ AFE & Wireless Comm.

Optionally single chip

Conclusion

- **Research for patients with paralysis**
  - Low-cost wearable BCI system
- **Propose CCA-Lite for low-complexity target identification**
  - Target selection time reduction : **93%**
  - ITR (Information Transfer Rate) improvement : **23%**
  - Total performance improvement (for single target identification time) : **22%**
- **Further work - support multi-ch EEG processing for better accuracy**
  - SoC (System-on-chip) design with AFE (Analog Frontend) + dedicated hardware accelerator

THANK YOU

Any questions or comments - ✉ jihoonkim@ewha.ac.kr