Brain - computer interfaces using capacitive measurement of visual or auditory steady-state responses

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Background

- Brain-computer Interface
  - Brain–computer interface (BCI) is an emerging technology for interacting with the external world through a nonmuscular communication channel, completely independent of the motor pathways of the neural system.
- Components of a BCI system
  - *Brain signal acquisition unit* for acquiring signals from the brain by electrodes placed on the user's scalp or cortical surface.
  - *Signal processing unit* for processing signals from the brain to extract specific signal features that reflect the user's intent, and subsequently can be used as commands or messages that operate devices.
  - *Application unit* for using the processed signals to drive an application such as virtual keyboard or external devices.

Background

- Importance of EEG electrodes
  - In the BCI systems, the signal quality is most influenced by EEG electrodes on the signal acquisition part.
  - In the design of practical BCI system, the design of EEG electrodes is crucial part for high fidelity signal recording.
- A kind of electrodes types
  - Conventional wet electrodes
  - Dry electrodes
  - Active electrodes
  - Advanced electrodes

wet electrodes

g.tec SAHARA dry electrodes

g.tec active electrodes

Research Purpose

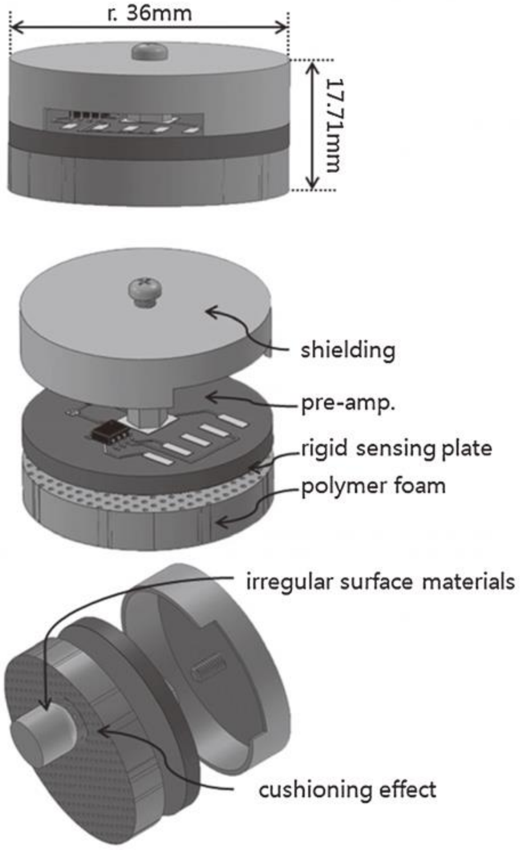
- Ideal electrodes
  - No require scalp/skin preparation
  - Short installation time
  - Comport experience for long time wearability
  - Look usual for practical BCI application
- Capacitive electrodes
  - A dry electrode, which does not require direct skin to electrode contact.
  - Removing scalp hair is not required.
  - Users are not made to feel uncomfortable.
- Research purpose
  - They introduced a *new capacitive electrode* that employs *conductive polymer-foam* as a sensing plate, instead of a rigid metal plate, in order to improve its performance in EEG measurement

Polymer foam-based capacitive EEG electrodes

- Principle
  - Capacitive electrodes record EEG signals by measuring capacitance that builds up between an individual's scalp surface and an electrode.
  - Capacitive EEG measurement is characterized by very high electrode impedance.
    - It is easy to develop as a form of active electrode in which high input-impedance pre-amplifiers are embedded
- Difficulty in measuring EEG using capacitive electrode
  - Rigid surface of a conventional capacitive electrode is unable to adapt to head topology
  - Human hair is thin and creates an irregular micrometer-wide air gap between the scalp and the electrode surface
  - Hair moves easily during signal measurements.

Polymer foam-based capacitive EEG electrodes

- Structure
  - Polymer foam
    - Foam consisted of polyolefine covered by polyurethane and coated with Ni/Cu to allow for electrical conductance
    - Provide a cushioning effect along the head curvature
    - Provide a stabilizing effect for the prevention of hair or electrode movement
    - Lower electrode–skin impedance (impedance difference of 100k-ohm for hairless and 2000k-ohm for hairy sites).
    - Higher signal-to-noise ratio and signal-to-error ratio
  - Pre-amplifier
    - Voltage follower circuit
    - TI OPA124(input resistance of 10^13 ohm and input capacitance of 1 pF)

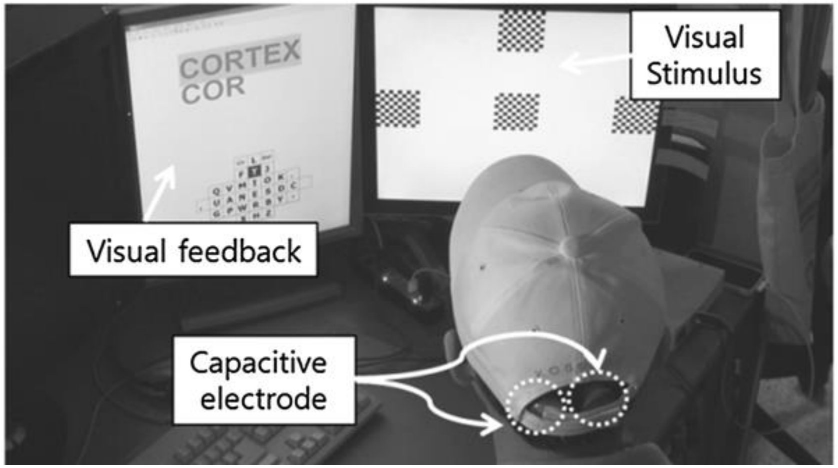


Test settings

- EEG acquisition device
  - Lab-made hardware module
  - It consists of a high-pass filter (0.05 Hz), low-pass filter (30 Hz), 60-Hz notch filter and an amplifier.
  - Signals digitized at a sampling rate of 512 Hz using an analogue-to-digital converter (NI DAQ Pad 6015).
  - Data loaded by Matlab data acquisition toolbox
- Subjects
  - five male participants ranging in ages from 28 to 31 (mean age 28.8 ± 1.25).
  - All participants were healthy and had normal hearing and normal or corrected to normal vision.
- Experiment paradigms
  - SSVEP(Steady-State Visual Evoked Potential) speller system
  - ASSR(Auditory Steady-State Response) binary decision system

SSVEP-based BCI test

- Test set-up
  - Stimuli were generated using Matlab with Psychotoolbox
  - Five checkerboard patterns flickered at 12, 7.5, 8.57, 6.67 and 5.45 Hz and corresponded to the commands ‘LEFT(L)’, ‘UP (U)’, ‘RIGHT (R)’, ‘DOWN (D)’ and ‘SELECT(S)’, respectively.
  - GUI was presented in the second screen right next to the stimulus screen.
  - Attached electrode positions : O1, O2, A2(Reference, standard ECG electrodes), Fpz(Ground, standard ECG electrodes)

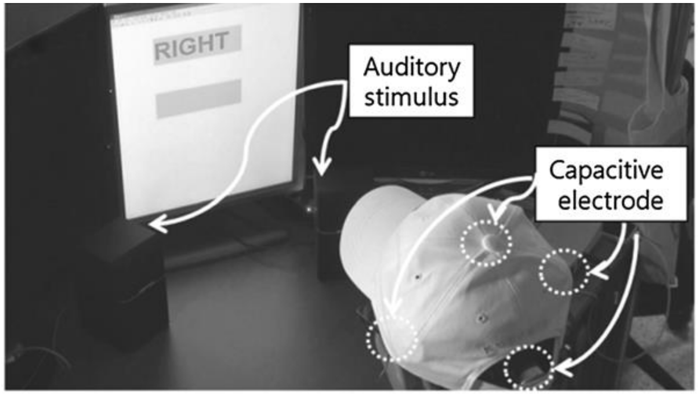


SSVEP-based BCI test

- Offline experiments
  - For optimizing the analysis window size
  - Participants were then asked to gaze on each stimulus for 10 s in a random fashion and repeated ten times without feedbacks. (5 classes x 10seconds x 10 repeated times)
  - They tested time window size from 5 to 10 s with 1 s time resolution in order to investigate time-sensitive changes of performance.
  - They employed the canonical correlation analysis (CCA) algorithm to find the maximal correlation between the EEG signal and signals corresponding to the SSVEP stimulus frequencies.
- Online experiments
  - subjects were asked to spell the words ‘BRAIN’, ‘CORTEX’ and ‘MEMORY’.
  - Visual and auditory feedback was provided in real time.

ASSR-based BCI test

- Test set-up
  - Auditory stimuli selection
    - Stimuli were generated using Matlab with periodic amplitude-modulated and pure sinusoidal tones.
    - Frequency ranges peaking around 40 Hz were shown to obtain higher ASSR signal-to-noise : 37 and 43 Hz modulation frequencies were selected
    - In order to make auditory stimuli easily distinguishable, 2.5 and 1 kHz carrier frequencies were selected
  - Left sound : 2.5kHz tone + 37Hz modulation frequency
    Right sound : 1kHz tone + 43Hz modulation frequency
  - Attached electrode positions : Oz, Cz, T7, T8, A2(Reference, standard ECG electrodes), Fpz(Ground, standard ECG electrodes)

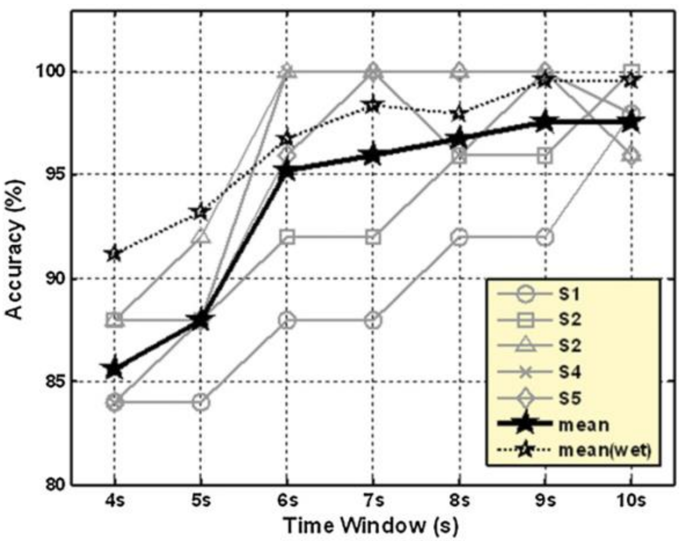


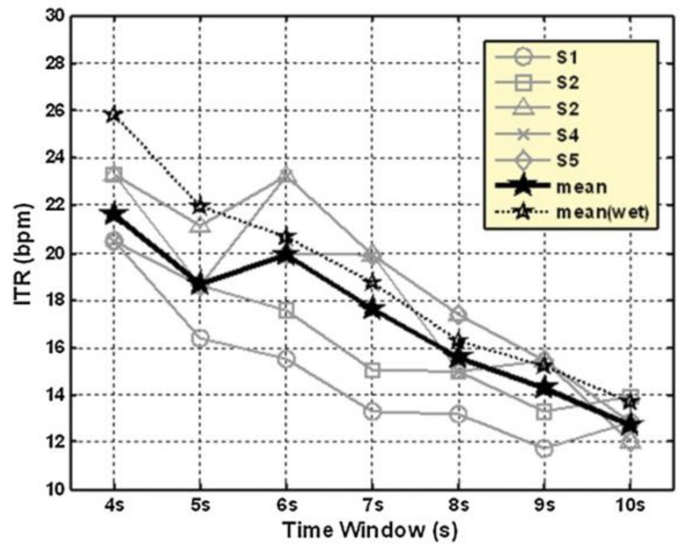
ASSR-based BCI test

- Offline experiments
  - For determine optimal analysis window size.
  - The participants were asked to concentrate on one of the stimuli (L or R) for 20 s and then repeated 50 times (2 classes x 20seconds x 25trials)
  - No feedback was given to subjects.
  - For the evaluation of classification, a 10-fold cross validation method was applied.(45 training trials + 5 test trials)
  - Feature extraction
    - They calculated frequency spectrums using a nonparametric periodogram method with a 1 s sliding time window and 50% overlap.
    - Spectral density of each electrode over stimulus frequency ±1 Hz range was extracted(36 ~ 38Hz, 42 ~ 44Hz) from the averaged frequency spectra.
    - Make feature vector.
  - Classification
    - Linear discriminant analysis (LDA) method
      (It guarantees maximal class separation by maximizing the ratio of between-class variation to within-class variation in our dataset)
  - Time window size of 5 to 20 s with 1 s time resolution was tested.
- Online experiments
  - A total of ten trials were performed of selective attention to either left or right stimuli.

SSVEP-based BCI Results

- Selection of time window size
  - Averaged classification accuracy for all subjects was 85.6%(4s), 88%(5s), 95.2%(6s) and 97.6%(10s)
  - Considering trade-offs between time window size and accuracy, ITRs, an analysis window size of 6 s was selected as optimal for all p.articipants





SSVEP-based BCI Results

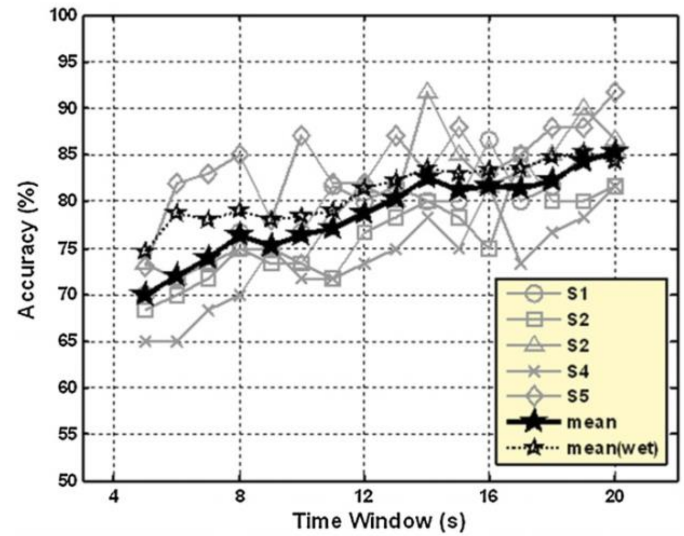
- Online experimental results
  - Considering our experimental results, we were able to confirm that our polymer foam-based capacitive coupled EEG electrode could be used for various SSVEP-based BCI applications.
  - EFF : minimum number of commands necessary to spell the target word divided by the number of commands issued during the run
  - www.youtube.com/watch?v=eFktIckFqac

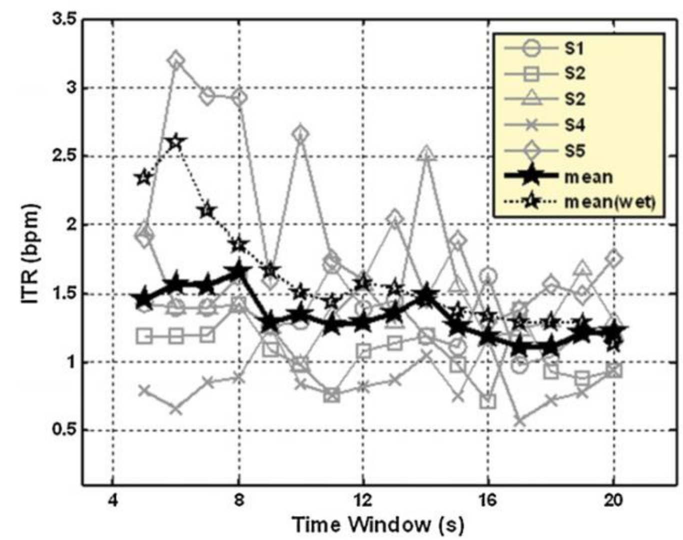
Table 1. The results of SSVEP-based online BCI experiments (ACC: accuracy in %, ITR: information transfer rate in bit min^{-1}, LPM: letters per minute in letter min^{-1} and EFF: efficiency in %).

Word	Sub.	Time Window	Input results (wrong underlined)	ACC (%)	ITR (bits min^{-1})	LPM (letters min^{-1})	EFF (%)
BRAIN	S1	6s	→↓B↓R←←A↑I↑←↓N	92.86	16.79	3.57	85.71
	S2	6s	↓→B↓R←←A↑I←N	100	23.22	4.17	100
		4s	↓↑↓→B↑↓↓R←←A↑I←←→N	83.33	14.50	4.17	66.67
	S3	5s	↓→B↓R←←A↑I←N	100	27.86	5	100
		6s	↓→B↓R←←A↑I←N	100	23.22	4.17	100
	S4	6s	↓→→→←←B↓R←←A↑I←N	87.5	15.67	3.13	75
	S5	6s	→↓B↓R←←←→A↑I←N	92.86	16.79	3.57	85.71
CORTEX	S1	6s	→→→C↓→↑↑O↓R↑↑TE↓↓←↑↓X	90.48	15.18	2.98	80.95
	S2	6s	→→→→←C↑→O↓R↑↑TE↓↓←X	94.74	18.18	3.16	89.47
	S3	4s	↓↑→→→→←C→→←↑O←←→→↓R↑↑TE↓↓ ↑↓←X	79.31	13.95	3.10	58.62
		5s	→→→C←↑→→O↓R↑↑T←→E↓↓←X	90.48	18.22	3.43	80.95
		6s	→→→C↑→O↓R↑↑TE↓↓←X	100	23.22	3.53	100
	S4	6s	→→→C↑→O←→↓R↑↑TE↓↓←X	94.74	18.18	3.16	89.47
	S5	6s	→→→C→↑O↓↓↑R↑↓↑↑TE↓→←↓←X	86.96	13.07	2.61	73.91
MEMORY	S1	6s	←↑ME←↓↑↑M→↑O↓R→→↓Y	94.44	17.95	3.33	88.89
	S2	6s	↑←ME↑←M↑→O↓↓↑R↓→→→←Y	90	14.88	3	80
	S3	4s	↑←ME↑←←→→←M↑←→→O↑↓↓→←R↓↓← →→←↑→→Y	75	11.37	2.81	50
		5s	↑←M↑↓E↑←M↑→O↓R↓→→→←Y	90	17.85	3.6	80
		6s	↑←ME↑←M↑→O↓R↓→→Y	100	23.22	3.75	100
	S4	6s	←↑ME←←→↑M→↑↑↑↓↓O↓R→→↓Y	86.36	15.01	2.73	72.73
	S5	6s	←↑ME←↑M←→→↑O↓→←R→→→↓←Y	86.36	15.01	2.73	72.73
Mean				91.21	17.78	3.41	82.42

ASSR-based BCI Results

- Selection of time window size
  - Classification accuracy increased with increased analysis time window size.
  - No longer increased after about 14 s.





ASSR-based BCI Results

- Online experimental results
  - Specificity (SPEC,) and sensitivity (SENS) were calculated by assuming positive to be left (L) and negative to be right (R).
  - The results obtained in this study are comparable to previously reported results from the same ASSR-based paradigm with conventional Ag/AgCl electrodes
  - www.youtube.com/watch?v=emKvgvKaHuw

Table 2. The results of ASSR-based online BCI experiments. (NUM: number of correct classification per total number of trials, SEPC: specificity, SENS: sensitivity and ITR: information transfer rate in bit min^{-1}). The wrong classification is underlined.

Sub.	Time window	Task	Classification Results	NUM (correct/total)	SPEC	SENS	ITR (bits min^{-1})
S1	14s	LLRRLRLRLR	LLLRLRRLRR	6/10	0.6	0.6	0.12
S2	14s	RRRLRLLLRL	LRRLLLLLLL	7/10	0.4	1	0.51
S3	14s	LRRLLRLRLR	LRLLLRRRLR	8/10	0.8	0.8	1.19
S4	14s	LLRRLRLLRR	LRRRLRRLRL	7/10	0.8	0.6	0.51
S5	14s	LLRRLRLRLR	LLRLLRRRLR	8/10	0.6	0.8	1.19
Mean				7.2/10	0.64	0.76	0.70

		Condition (as determined by "Gold standard")		
		Condition positive	Condition negative	
Test outcome	Test outcome positive	**True positive(TP)**	**False positive(FP)** (Type I error)	Precision (Positive predictive value) =TP/(TP+FP)
	Test outcome negative	**False negative(FN)** (Type II error)	**True negative(TN)**	Negative predictive value =TN/(TN+FN)
		Sensitivity = TP/(TP+FN)	**Specificity** = TN/(FP+TN)	Accuracy =(TP+TN)/(P+N)

Discussion

- Comparison of various electrodes
  - MEMS/carbon nanotube-based electrodes : slightly invasive
  - Fabric-based electrodes : difficulty measuring EEG signals at sites covered with hair.
  - Hybrid-type or spring loaded Electrode :still require preparation in order to ensure contact between the finger and scalp
  - Capacitive electrodes : do not require any electrical contact between the sensor and scalp
    - Still need for improvements in EEG sensing despite high source impedance, head curvature and undefined contact area due to hair.

Conclusion

- They investigate whether a newly developed polymer foam-based capacitive electrode can be used in steady-state response-based BCI applications.
- Using our capacitive electrode, EEG was successfully measured without direct scalp contact in subjects wearing electrode-equipped baseball caps.

Appendix

- Canonical Correlation Analysis
  - CCA is a multivariable statistical method used when there are two sets of data, which may have some underlying correlation.

$$y(t) = \begin{pmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \\ y_4(t) \\ y_5(t) \\ y_6(t) \end{pmatrix} = \begin{pmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ \sin(4\pi f t) \\ \cos(4\pi f t) \\ \sin(6\pi f t) \\ \cos(6\pi f t) \end{pmatrix}, \qquad t = \frac{1}{S}, \frac{2}{S}, \ldots, \frac{T}{S}$$

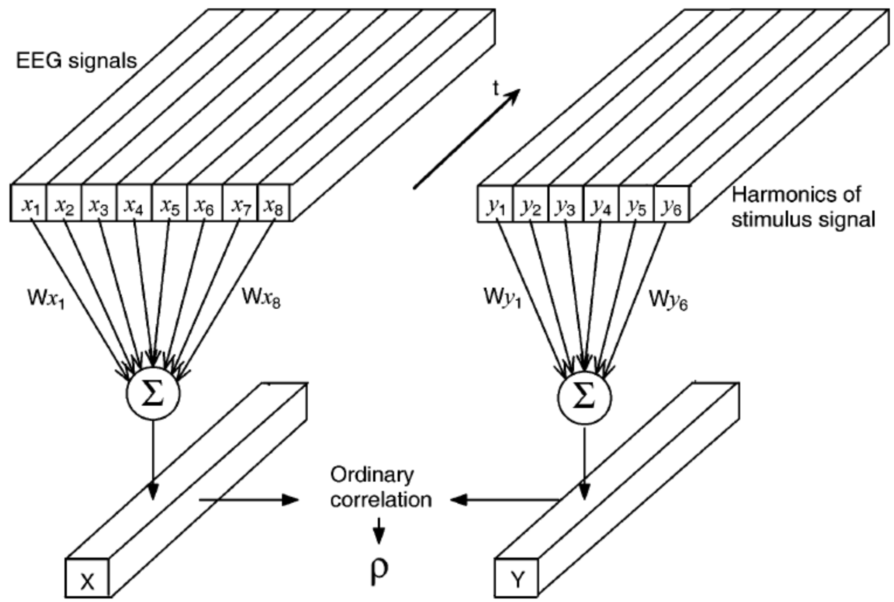


Fig. 1. An illustration for usage of CCA in EEG signal analysis. $x_1, \ldots, x_8$ are signals from 8 EEG channels and $y_1, \ldots, y_6$ are Fourier series of a given frequency period signal. The CCA finds the linear combination coefficients $w_{x_1}, \ldots, w_{x_8}$ and $w_{y_1}, \ldots, w_{y_6}$, which gives the largest correlation between X and Y. For brief statement, we omit the variable t. The figure uses [13] for reference.