EEG-Based Brain-Computer Interfaces for Communication and Control

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뇌-컴퓨터 접속(BCI) 연구의 필요성


종합
NEWS

호킹박사 `컴퓨터목소리` 마저…
병세 악화로 1분에 한 단어밖에 말 못해

기사입력 2012.01.06 17:10:54 | 최종수정 2012.01.06 17:33:27

기사 | 나도 한마디 | [이벤트] 다양한 이벤트가 언제나 한가득

`휠체어 위의 천재` 스티븐 호킹 박사(69)가 지난 35년간 컴퓨터에 의존해 내왔던 목소리를 잃을 위기에 처했다.

영국 일간지 데일리메일은 5일 호킹 박사가 1분에 1개 단어밖에 말할 수 없는 상태에 처했다고 밝혔다.

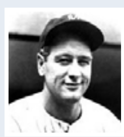
그는 지난 50년간 근위축성측색경화증(루게릭병)을 앓았으며 1985년에는 폐렴에 따른 후유증으로 목소리까지 잃었다.

루게릭병에 걸리면 온몸의 근육 전체가 서서히 마비된다. 호킹 박사는 지금까지는 손가락 2개를 움직일 수 있어 컴퓨터 화면에 나타난 글자를 손끝으로 눌러 문장을 만들어낼 수 있었다. 이렇게 만든 문장을 컴퓨터가 소리로 합성하는 방법으로 그는 그동안 목소리를 내왔다.

데일리메일은 "루게릭병이 심각히 진행돼 호킹 박사는 이제 얼굴 근육과 신경마저 마비된 상태"라며 "이 장치를 더 이상 사용할 수 없어 언어를 상실할 위기에 처했다"고 밝혔다.

호킹 박사의 대학원생 제자인 샘 블랙번은 "호킹 박사가 이 장치를 계속 이용하기를 바란다"면서도 "불가능하다면 눈과 안면 움직임 인식, 뇌 스캐닝 등 대체장치를 개발해야 할 것"이라고 밝혔다.

(2012년 1월 6일, 중앙일보)



헨리 루이스 루 게릭
(Henry Louis Lou Gehrig)

1903.06.19 -1941.06.02

야구선수

근위축성 측색경화
(Amyotrophic Lateral Sclerosis: ALS)

- 매년 140,000 – 210,000명 발병
- 부분 혹은 전신의 운동기능 상실
- 본인의 의지로 타인과 의사소통 어려움

뇌-컴퓨터 접속(BCI) 연구의 필요성

산업재해와 사고
(한국 OECD 국가 중 교통사고율 1위)

급성 심장질환
(서구화된 식습관, 고령화)

퇴행성 뇌질환
(ALS, 파킨슨병, 뇌졸중, 진행성연수마비, 척수근육위축)

- 신체 일부 혹은 전신의 기능 상실
- 심할 경우 식물인간
- 매년 증가

- 미국에서만 200만 명 이상의 신경계 손상 환자들이 보고 (Carter, 1997)
- 국내에서 언어를 직간접적으로 생성하지 못하는 환자의 수는 약 10만 명 (임창환, 2010)

의사소통이 불가능하거나 제한적
의료 및 간병 서비스 어려움

뇌-컴퓨터 접속(BCI)

뇌-컴퓨터 접속 (Brain-Computer Interface: BCI)
또는
뇌-기계 접속 (Brain-Machine Interface: BMI)

뇌신경계로부터 측정된 신호를 분석하여 컴퓨터 또는 외부기기 제어

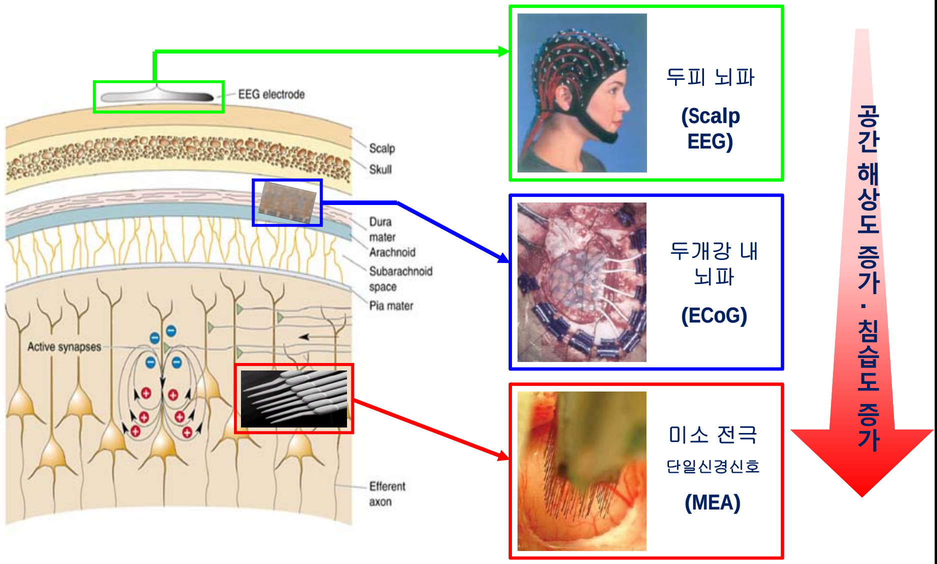
사용자의 의사를 외부에 전달하기 위한 기술

뇌의 신호

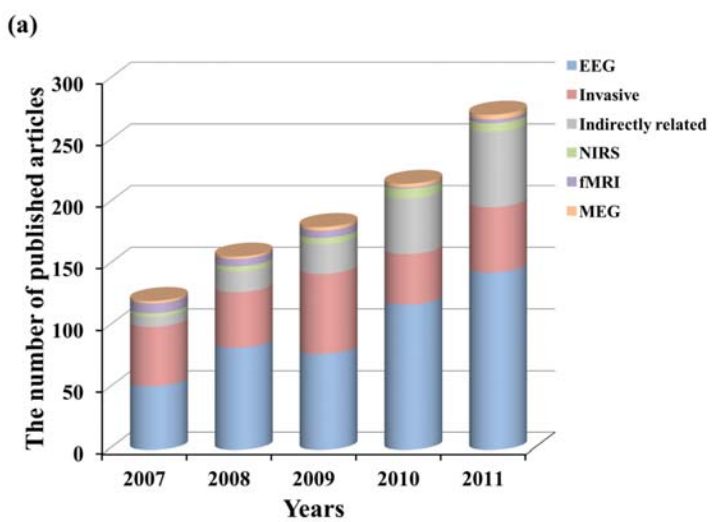
일종의 번역기

의사 소통 수단

뇌-컴퓨터 접속(BCI)



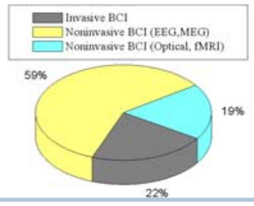
Research Trends in BCI



(Hwang et al., submitted)

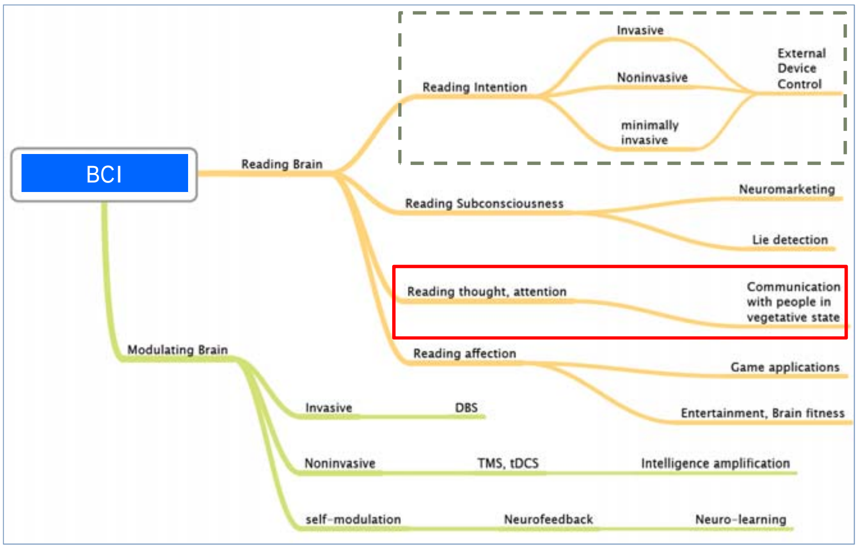
뇌-컴퓨터 접속(BCI)

비침습적 BCI		침습적 BCI
80%	**연구의 활성화 정도**	20%
공간 해상도가 낮음	**문제점**	수술 필요
안전함	**안전성**	생체적합성 문제



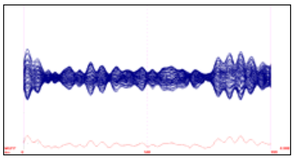
- Invasive BCI: still risky, hard to be applied to human being
- Noninvasive BCI (fMRI, MEG, NIRS): impractical (mobility, price)
- EEG-based BCI: most preferred

Classification of BCI Technology

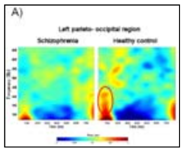


넓은 의미에서의 뇌-기계 접속 분야의 분류(2012년 기술영향평가-BMI 정의를 개념도로 그림)

Basic Concepts



EEG recording
Training phase



Feature extraction
Database construction

RT recording

Real-time feature extraction

Comparison with database

Real-time classification

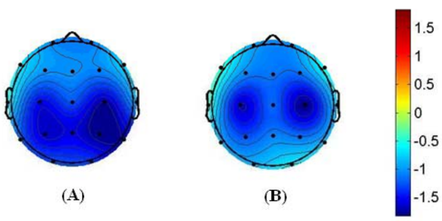
Command signal

Manipulation of external devices, Generation of messages

1. Mu-rhythm based BCI (motor imagery)

- Event-related desynchronization (ERD) & Event-related synchronization (ERS) around the motor cortex areas generated by motor imagery of hands, foots, tongue, etc.

-Short reaction time, independent BCI, adequate for device control
-Low classification accuracy, highly dependent on subjects, hard to train



Event-related desynchronization during motor imagery of left hand: (A) motor imagery with visual stimuli; (B) motor imagery without visual stimuli

(Im, J. Biomed. Eng. Res., 2010)

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Neurofeedback-based Motor Imagery Training for BCI

- Motor Imagery is defined as mental simulation of a kinesthetic movement.

- Many individuals (including patients) have difficulty in getting used to the feel of motor imagery, since most people do not easily recognize how they can have a concrete feeling of motor imagery and tend to imagine the images of moving their hands or legs instead (visual motor imagery).

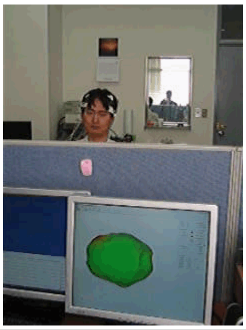
- We developed a kind of neurofeedback systems to train motor imagery by presenting participants with time-varying activation maps of their brain, using a real-time cortical rhythmic activity monitoring system.

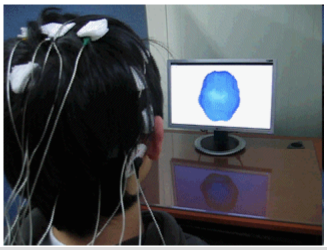
- Half of ten human volunteers were asked to imagine either left or right hand movement while they were watching their cortical activation maps through the real-time monitoring system.

- During the experiment, the participants were asked to continuously try to increase their mu-rhythm activations (8-12 Hz) around the sensorimotor cortex areas.

(Hwang, Kwon, Im, J. Neurosci. Meth., 2009)

Real-time Rhythmic Activity Monitoring System





Real-time cortical mu (8-12 Hz) activity imaging

Real-time cortical alpha (8-13 Hz) activity imaging

(Im et al., Physiol. Meas., 2007)
(Lee et al., Arch. Phys. Med. Rehab., 2012)
(Shin et al., NeuroRehab., 2012)

Real-time connectivity monitoring at 30 Hz (Gamma)

(Hwang, Im et al., Med. Biol. Eng. Compt., 2011)

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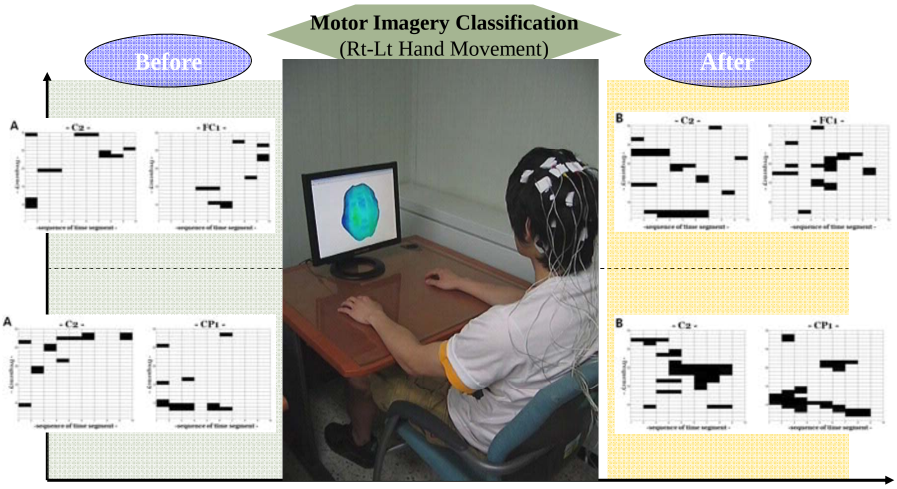
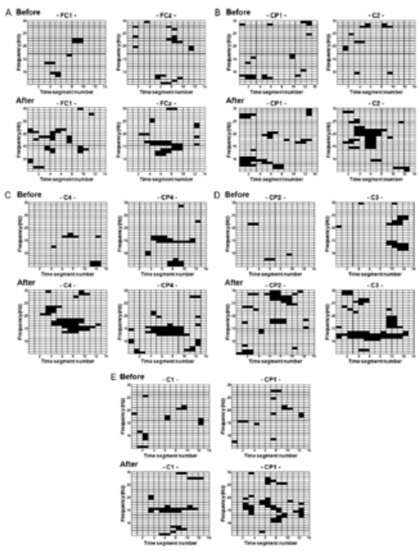
Neurofeedback-based Motor Imagery Training for BCI



Motor Imagery Training (**0.5 hrs**)

(Hwang, Kwon, Im, J. Neurosci. Meth., 2009)

Motor Imagery Training for BCI



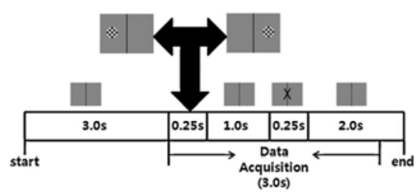


Table 2
Changes in classification accuracy before and after motor imagery training (or first and second EEG recordings in control group). We first selected the two time–frequency combinations that had the smallest *p*-values as the features for classifying left and right hand motor imagery. A Euclidean distance algorithm was then used to estimate the classification accuracy.

Trained group			Control group		
Participant	Before (%)	After (%)	Participant	First (%)	Second (%)
EK	60	77	JI	57	52
GS	62	67	BK	60	54
DK	59	72	HJ	73	70
KS	58	72	TI	67	75
JN	55	69	SJ	64	66
Mean	58.8	71.4	Mean	64.2	63.4

(Hwang, Kwon, Im, J. Neurosci. Meth., 2009)

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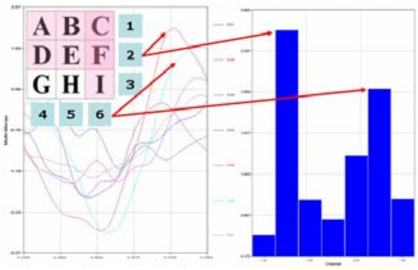
2. P300-Based BCI

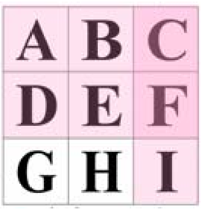
-High accuracy, less dependent upon subjects, easy to train



An example of P300-based BCI:
Results of a test experiment

Austria Guger Technologies – P300 speller

P300-based BCI

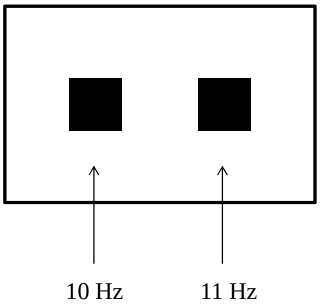


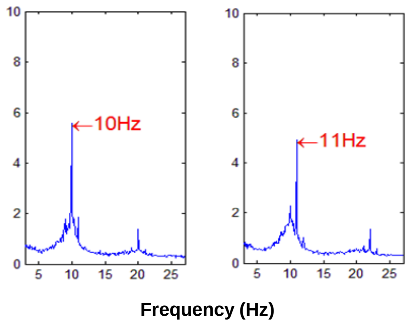
P300-based BCI in Hanyang University
Collaboration with RIKEN, Japan

(Hwang et al., in prep.)

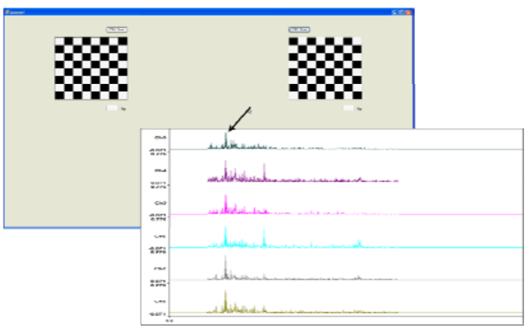
SSVEP-based BCI

Steady-state visual evoked potential (SSVEP)
a periodic brain response elicited by the continuous presentation of a visual stimulus flickering or reversing at a certain frequency





SSVEP-based BCI



Software for presenting visual stimuli eliciting steady-state visual evoked potential (SSVEP) and real-time monitoring of frequency spectrum

U of Willhelm (Germany)

SSVEP-based BCI

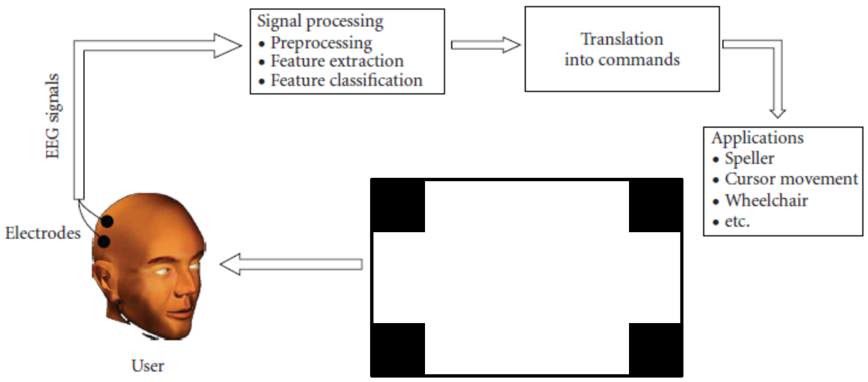


FIGURE 1: Functional model of an SSVEP-based BCI.

From (Zhu et al., 2010)

Computer Monitor as a Rendering Device

Computer monitor has been used in most SSVEP based BCI studies.

Although SSVEP can be elicited by a broad range of frequencies (ranging from 1 Hz to 60 Hz), the available frequencies in practical BCI applications are often restricted by several factors.

1. The frequencies that elicit strong SSVEP responses are highly dependent upon the participants, as well as various properties of the visual stimuli, such as color, size, and contrast.
2. The use of two frequencies, F_1 and F_2, in the same experiment has been typically avoided when F_1 is a multiple of F_2 or vice versa because of the harmonic SSVEP responses.
3. The frequencies in the alpha band (8-13 Hz) should be carefully selected because its use has been attributed to a considerable number of false positives.
4. It is rare but sometimes possible that some visual stimuli with flickering frequencies in the 15 – 25 Hz frequency band may provoke epileptic seizures.
5. When using a monitor as a rendering device, stimulation frequencies have to be set as sub-harmonics of the monitor refresh rate (usually 60 Hz) to attain accurate SSVEP responses.

Increasing the Number of Stimuli with Limited Number of Frequencies

When the visual flicking stimuli are presented through a computer monitor, available frequencies are limited due to the intrinsic frequency of the monitor (usually 60 Hz).

Available Frequencies (examples): 60, 30, 20, 15, 10, 6.66, 6, 4.285, 3.75, etc.
Theta band has been most frequently used (alpha band is generally too sensitive; frequency bands over alpha band – potentially risky)

One of the challenging issues in SSVEP-based BCI studies is to make the best use of available frequencies in order to generate various visual stimuli.

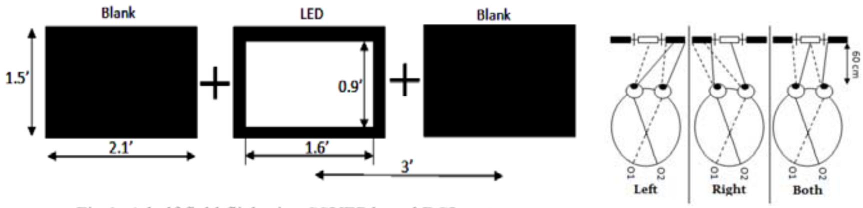
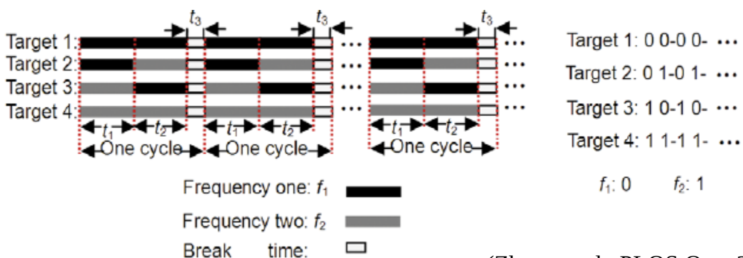


Fig.1 A half field flickering SSVEP based BCI system

Two visual stimuli generated using a single frequency
It is difficult to generate multiple stimuli

(Punsawad et al., IEEE EMBS, 2011)

Increasing the Number of Stimuli with Limited Number of Frequencies



(Zhang et al., PLOS One, 2011)

This stimulation method can generate N^2 visual stimuli using N frequencies.
Visual cue is needed – continuous operation is not possible

Increasing the Number of Stimuli with Limited Number of Frequencies: Dual Frequency Stimulation

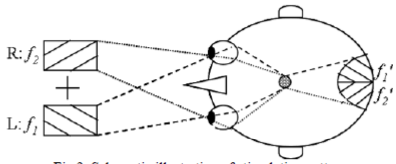


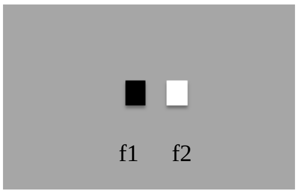
Fig.2. Schematic illustration of stimulation pattern.

can generate N^2 stimuli using N frequencies

Half-field stimulation pattern

(Yan et al., IEEE EMBS, 2009)

Presenting dual frequencies might increase the number of possible stimuli (Shyu et al., Neurosci. Lett., 2010).

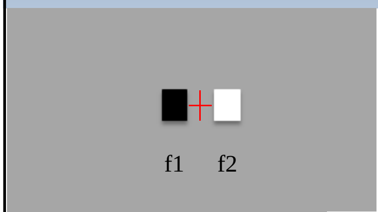


Example:
f1 = 3 Hz, f2 = 3.33 Hz
f1 = 3 Hz, f2 = 3.75 Hz
f1 = 3 Hz, f2 = 4.285 Hz
f1 = 3.33 Hz, f2 = 3.75 Hz
f1 = 3.33 Hz, f2 = 4.285 Hz
f1 = 3.75 Hz, f2 = 4.285 Hz

can generate $_NC_2$ stimuli using N frequencies

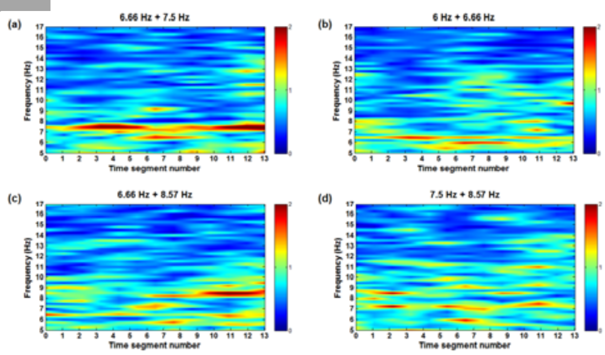
4 frequencies → 6 independent stimuli

Problem of Conventional Approach



Yan et al. (2009) and Shyu et al. (2010) commonly pointed out the limitation of their methods

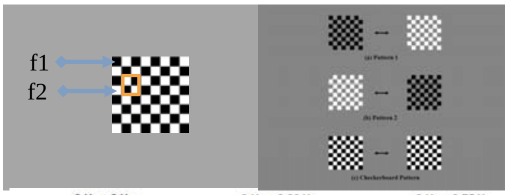
Attention Shift



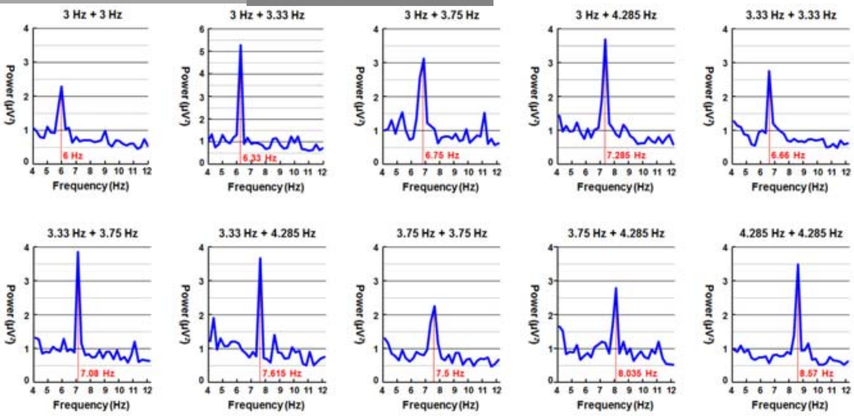
(Hwang et al., IEEE T-BME, in revision)

Proposed Visual Stimuli

(Hwang et al., IEEE T-BME, in revision)

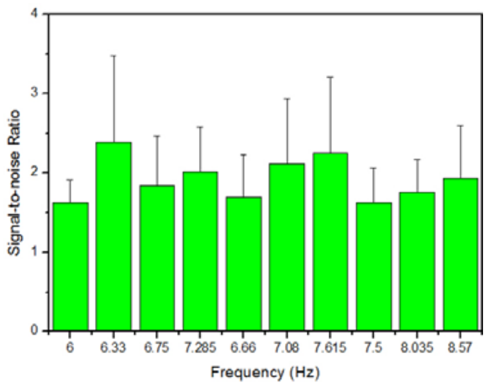


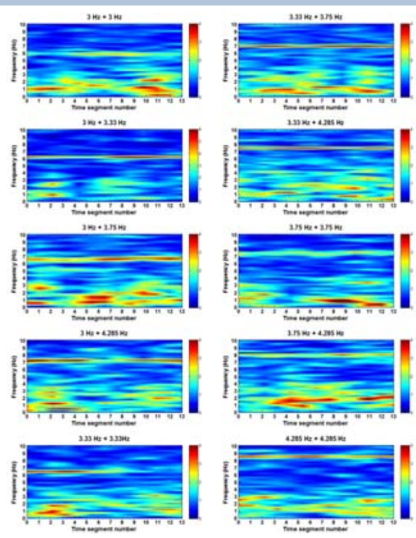
4 frequencies → 10 independent stimuli



Validation Using SNR Value

Averaged SNR value (11 subjects)





(Hwang et al., IEEE T-BME, in revision)

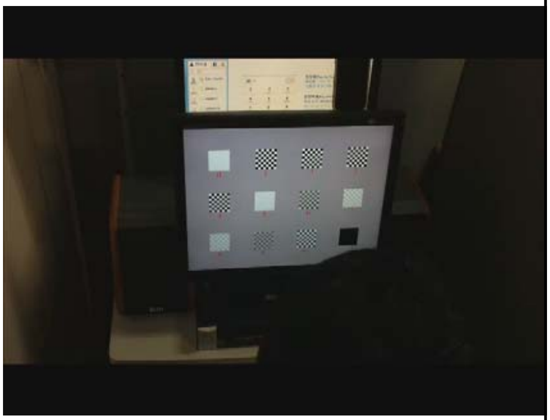
Dual-frequency SSVEP BCI

- **Online Experiment**

: We tested ten sets of 5-digit numbers, when the time period required to spell one number was set to 4-6 s.

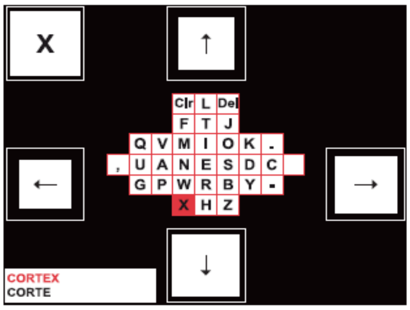
TABLE II
RESULTS OF THE ONLINE EXPERIMENTS

Participants	Time Period (s)	Correct/ Total	Accuracy (%)	ITR (bits/min)	Efficiency
P12	4	67/72	93.06	44.72	0.072
P13	6	73/84	86.90	25.72	0.044
P14	4	68/74	91.89	43.48	0.070
P15	6	79/96	82.29	22.99	0.039
P16	4	70/78	89.74	41.29	0.063
P17	5	80/98	81.63	27.14	0.050
P18	4	67/72	93.06	44.72	0.063
P19	6	74/86	86.05	25.19	0.058
P20	5	80/98	81.63	27.14	0.037
P21	5	74/86	86.05	30.23	0.056
Mean			87.23	33.26	0.056
S.D.			4.55	9.07	0.012

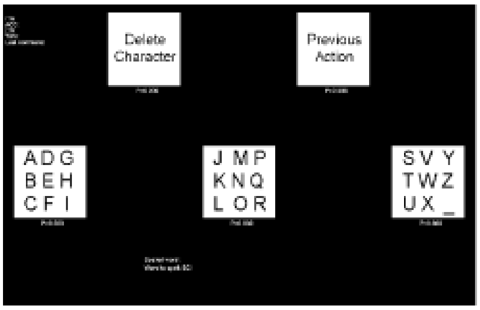


(Hwang et al., IEEE T-BME, in revision)

SSVEP-Based Mental Speller



(Volosyak et al., 2011)

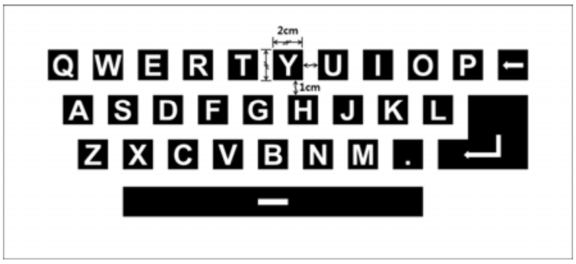


(Cecotti et al., 2010)

Why SSVEP-based Mental Speller?
- No training is required!!
- Simple classification algorithm

SSVEP-Based Mental Speller

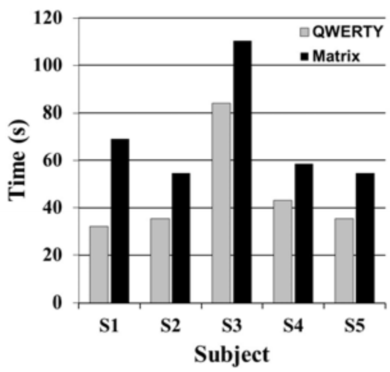
- Conventional electroencephalography (EEG) mental spelling systems based on P300 or steady-state visual evoked potential (SSVEP) generally arrange characters alphabetically in a rectangular 2-D array structure, which makes it difficult for the users to realize the locations of target characters easily.
- Considering that acquired factors are the main cause of disabilities for disabled individuals, the majority of the target subjects are more familiar with a QWERTY style keyboard not having a rectangular array structure.
- In this study, we implemented an SSVEP-based mental spelling system adopting a QWERTY style keyboard layout with 30 LEDs flickering with different frequencies.



(Hwang et al., J. Neurosci. Meth., 2012)

SSVEP-Based Mental Speller

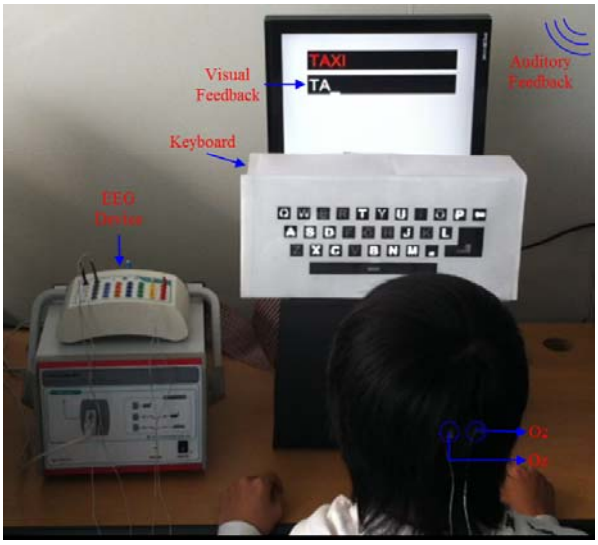
-Various factors influencing the detection accuracy, such as light source arrangement, stimulating frequencies, recording electrodes, and visual angle, were taken into account for implementing our pilot system.
-For the verification of the feasibility of the system, five participants took part in the offline experiments.



Time taken to visually scan 15 English words (68 characters)

(Hwang et al., J. Neurosci. Meth., 2012)

SSVEP-Based Mental Speller



(Hwang et al., J. Neurosci. Meth., 2012)

SSVEP-Based Mental Speller

Watch this video at
http://www.youtube.com/watch?v=uunf3FDfEno

(Hwang et al., J. Neurosci. Meth., 2012)

SSVEP-Based Mental Speller

Word	5 s Input Results (wrong underlined)	5 s Correct/ Total	6 s Input Results (wrong underlined)	6 s Correct/ Total	7 s Input Results (wrong underlined)	7 s Correct/ Total
WOMEN	WU←P←OMEM←N	8/11	WOMEN	5/5	WOMEN	5/5
DESK	DESQ←K	5/6	DES_←SK	5/6	DES_←SK	5/6
WATER	WATER	5/5	WATER	5/5	WAG←TER	6/7
HAND	HAND	4/4	HAND	4/4	HAND	4/4
MEMORY	L←L←MEMORY	8/10	MEMORY	6/6	MEMORY	6/6
ZONE	ZONE	4/4	ZONY←E	5/6	ZSR←←ONE	6/8
BABY	U←BAW←R←BD←Y	8/12	BABX←Z←Y	6/8	BABY	4/4
FACE	FACE	4/4	R←FACE	5/6	FAC_←CE	5/6
TAXI	TAXL←I	5/6	TAXI	4/4	TAXI	4/4
JUNE	JUNE	4/4	JUR←NE	5/6	M←JUNE	5/6
QUICK	QUICK	5/5	QUICZ←M←K	7/9	QO←UICK	6/7
VIDEO	VIDE_←O	6/7	VIA←N←DEO	7/9	VIU←DEO	6/7
GOLF	GOLF	4/4	GOLG←F	5/6	GOLF	4/4
HOUR	T←HOUG←R	6/8	HOUR	4/4	HOUR	4/4
PENCIL	PY←ENCIL	7/8	PENM←CZ←IL	8/10	PENI←CIL	7/8
Total		83/98		81/94		77/86
Accuracy (%)		84.69		86.17		89.53
ITR (bits/min)		42.55		36.55		33.55
LPM (letters/min)		10.16		8.62		7.64

(Hwang et al., J. Neurosci. Meth., 2012)

SSVEP-Based Mental Speller

- Online Experimental Results

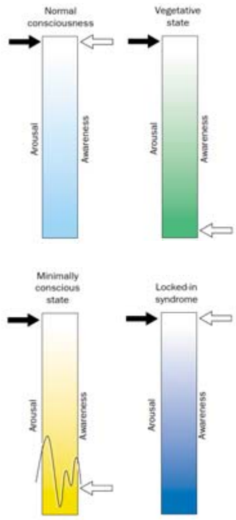
Participants	Time Period (s)	Correct/ Total	Accuracy (%)	ITR (bits/min)	LPM (letters/min)
P5	5	83/98	84.69	42.55	10.16
	6	81/94	86.17	36.55	8.62
	7	77/86	89.53	33.55	7.64
P6	4	91/114	79.82	48.02	11.97
	5	69/70	98.57	56.75	11.83
	6	68/68	100	49.07	10
P7	6	78/88	88.64	38.44	8.86
P8	6	84/100	84	34.95	8.40
P9	6	90/112	80.36	32.38	8.04
P10	6	84/100	84	34.95	8.40
	Mean		**87.58**	**40.72**	**9.39**
	S.D.		6.9	8.12	1.54

LPM of 9.39 is one of the best results reported in BCI literatures!

(Hwang et al., J. Neurosci. Meth., 2012)

Necessity of Patient-Specific BCI

Neurodegenerative Disorder (e.g. ALS)



Eyeball movement

Visual BCI
Eye-tracker

Abnormal eye movements (Donaghy et al., 2011)

Hard to control eyeball or eyelids

Completely Locked-in State (CLIS)

Normal auditory function

BCI Paradigm Based on Auditory Selective Attention

Most of the mental tasks and paradigms use visual stimuli, visual feedback, or both and are thereby applicable only to patients whose visual function is not impaired.

In practice, however, some patients with severe neurological disorders, such as ALS and completely locked-in state (CLIS), often have difficulty controlling their voluntary extraocular movements or fixing their gaze on specific visual stimuli.

Even for those who have normal visual function, gazing at stimuli for a long time can easily cause fatigue or loss of concentration.

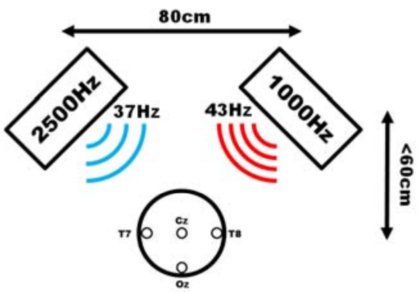
EEG signals recorded at frontal electrodes can be contaminated by electrooculogram (EOG) elicited by eye-blinking and eyeball movements. A recent experimental study demonstrated that the performance of the P300-based speller paradigm can be substantially influenced by eye gaze, which strongly suggests that the use of visual stimuli or cues might not be appropriate for those who have difficulty in gazing at specific target stimuli.

developing new BCI paradigms that are not dependent on visual stimuli remains one of the challenging issues in modern BCI research

(Kim et al., J. Neurosci. Meth., 2011)

BCI Paradigm Based on Auditory Selective Attention

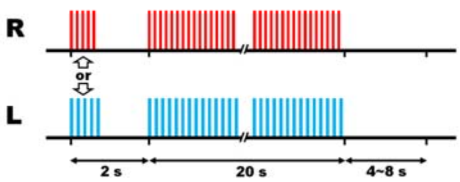
In the present study, we investigated whether ASSR can be a feasible feature for a practical BCI system by implementing a modified BCI paradigm to classify one's auditory selective attention and by evaluating the classification accuracy of the BCI system.



(Kim et al., J. Neurosci. Meth., 2011)

BCI Paradigm Based on Auditory Selective Attention

- **Experimental protocol**



- Total 50 trials (2 sessions)
  - 25 trials per session (10 min)
  - 25 trials per direction

- Six participants were instructed to close their eyes and concentrate their attention on either auditory stimulus according to the instructions provided randomly through the speakers during the inter-stimulus interval.
- **Data acquisition and processing**
  - Sampling frequency = 512 Hz
  - The power spectrum density were calculated using fast Fourier transform (FFT) with 1 *s* sliding window (50% overlap) and was averaged over time

(Kim et al., J. Neurosci. Meth., 2011)

BCI Paradigm Based on Auditory Selective Attention

EEG signals were recorded at multiple electrodes mounted over the temporal, occipital, and parietal cortices.

We then extracted feature vectors by combining spectral power densities evaluated at the two beat frequencies.

As candidates of feature vectors, we first evaluated the EEG spectral densities of each electrode averaged over 37 ± 1 Hz (denoted as Cz_{37}, Oz_{37}, $T7_{37}$, $T8_{37}$) and 43 ± 1 Hz (Cz_{43}, Oz_{43}, $T7_{43}$, $T8_{43}$). We also evaluated the ratios between all possible pairs of spectral densities evaluated at the same modulation frequency ($Cz_{37}/T7_{37}$, $Cz_{37}/T8_{37}$, Cz_{37}/Oz_{37}, $T7_{37}/T8_{37}$, $T7_{37}/Oz_{37}$, $T8_{37}/Oz_{37}$, $Cz_{43}/T7_{43}$, $Cz_{43}/T8_{43}$, Cz_{43}/Oz_{43}, $T7_{43}/T8_{43}$, $T7_{43}/Oz_{43}$, $T8_{43}/Oz_{43}$) as well as the ratios between the spectral powers of each electrode evaluated at different modulation frequencies (Cz_{37}/Cz_{43}, $T7_{37}/T7_{43}$, $T8_{37}/T8_{43}$, Oz_{37}/Oz_{43}).

(Kim et al., J. Neurosci. Meth., 2011)

BCI Paradigm Based on Auditory Selective Attention

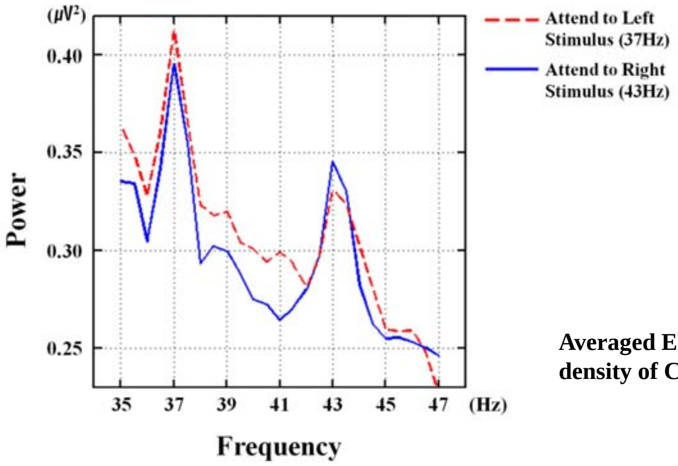
- **Classification strategies**
  - Classifications was done using *Euclidean distance* between the feature sets.

$$d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2+(q_2-p_2)^2+\cdots+(q_n-p_n)^2} = \sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}$$

  - The effect of *feature numbers*(up to three) and *analysis window* (2 ~ 20 *s*) were investigated.
  - 10-fold cross-validation was done separately for each of all possible feature sets.

(Kim et al., J. Neurosci. Meth., 2011)

BCI Paradigm Based on Auditory Selective Attention

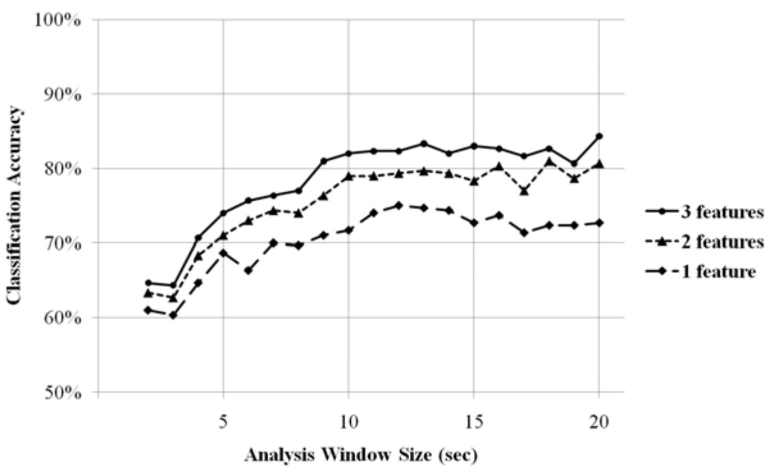


Averaged EEG spectral density of Cz electrode

The EEG spectral density was modulated by auditory selective attention to a specific sound source, demonstrating that switching attentions between two different sounds would generate classifiable feature vectors

(Kim et al., J. Neurosci. Meth., 2011)

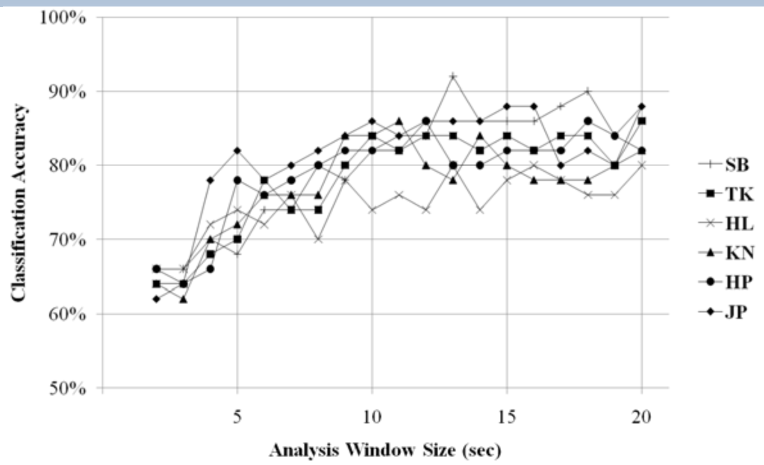
BCI Paradigm Based on Auditory Selective Attention



Effect of feature numbers and analysis windows

(Kim et al., J. Neurosci. Meth., 2011)

BCI Paradigm Based on Auditory Selective Attention



Classification accuracy of each participant

- Average classification accuracy : **85% (80 ~ 92%)**
- Analysis window size with maximum classification accuracy : **14.00 ± 2.94 *s***

(Kim et al., J. Neurosci. Meth., 2011)

BCI Paradigm Based on Auditory Selective Attention

Online BCI system:
A world-first ASSR-based BCI system

Classification accuracy = 71.4%

Potential Application: advanced ALS patients, completely locked-in states (CLIS) patients who has difficulty in controlling eye gaze

You can watch the full video at http://cone.hanyang.ac.kr

(Kim et al., J. Neurosci. Meth., 2011)