Brain and Cognitive Engineering: New Challenges in Multidisciplinary Research

Department of Brain and Cognitive Engineering,
Korea University

Seong-Whan Lee

April 27, 2012

History of Department of BCE

- Dec. 2008 Final approved for World Class University (WCU) project
- Jan. 2009 Three foreign scholars joined (H. Bülthoff, A. Jain, S. Jackson)
- Apr. 2009 Approved to launch WCU Dept. of BCE
- May 2009 Accepted new students for Fall semester, 2009
- Aug. 2009 Two foreign scholars joined (C. Koch, S. Edelman)
- Sep. 2009 Three new faculty members joined (S.-H. Kim, S.-P. Kim, J.-H. Lee)
- Sep. 2009 Begin WCU Dept. of BCE program at KU graduate school
- Sep. 2009 Researches and lectures by foreign scholars in 1st year of WCU program
- Dec. 2009 Accepted new students for Spring semester, 2010
- Mar. 2010 Two new faculty members joined (J.-H. Kwag, C. Wallraven)
- Jun. 2010 Accepted new students for Fall semester, 2010
- Sep. 2010 Researches and lectures by foreign scholars in 2nd year of WCU program
- Dec. 2010 Accepted new students for Spring semester, 2011
- Mar. 2011 Two new faculty members joined (J.-S. Park, J.-H. Han)
- Sep. 2011 Researches and lectures by foreign scholars in 3rd year of WCU program
- Sep. 2011 Two new foreign scholars joined (A. Yuille, D. Kersten)
- Dec. 2011 Accepted new students for Fall semester, 2011
- Mar. 2012 One new foreign scholar joined (K.-R. Müller)
- Mar. 2012 Two new faculty members joined (D.-J. Kim, B.-K. Min)

Dept. of Brain and Cognitive Engineering

- Established: September 1, 2009
  - Supported by World Class University (WCU) Project funded by the Ministry of Education, Science and Technology, Korea
- Major fields of study

Integrated Master and Ph.D. / Ph.D.	**Cognitive Brain Science**
	Brain-Computer Interface
	Brain Imaging Engineering

- Faculties
  - 18 faculty members
    (cross-disciplinary: Computer Science, Electrical Engineering, Cognitive Science, Neuroscience, Biology)

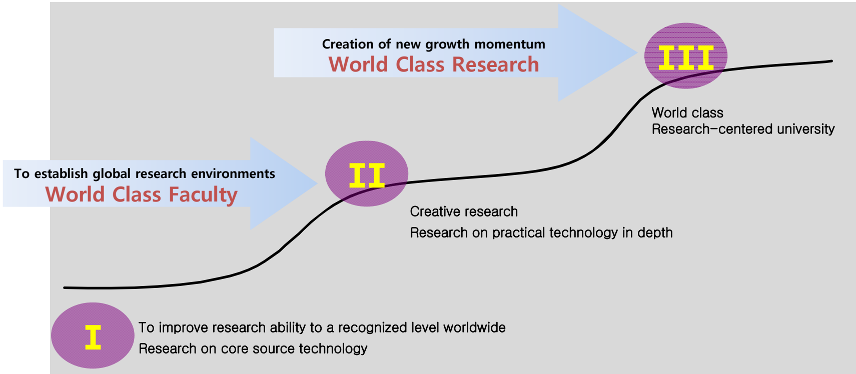
Educational Objectives

Vision

To invite worldwide distinguished scholars → Research on globally advanced technology →

To raise creative excellent human resources → To establish the research network with global research organizations →

To establish worldwide top research group in brain and cognitive engineering



International Scholars

Heinrich H. Bülthoff
Director, Max Planck Institute for Biological Cybernetics
Biological Cybernetics, Psychophysics, Cognitive Science

Anil K. Jain
University Distinguished Professor, Michigan State University
Biometrics, Pattern Recognition and Image Processing

Daniel Kersten
Professor, University of Minnesota
Visual Perception, Biology

Alan L. Yuille
Professor, UCLA
Neural Modeling, Mathematical Models of Cognition, Computational Vision

Klaus-Robert Müller
Professor, Berlin Institute of Technology
Brain-Computer Interface, Machine Learning, Neuroscience

Other Faculty Members

Hae-Chang Rim
Natural Language Processing,
Information Search, Artificial Intelligence

Chang-Hun Kim
Virtual Reality,
Computer Graphics

Seong-Whan Lee
Pattern Recognition,
Brain-Computer Interface

Ji-Chae Jeong
fNIRS, fOCT,
Intrabody Communications

Sang-Hee Kim
Functional Neurochemical Imaging,
Mechanism of Cognition and Emotional Disturbance

Sung-Phil Kim
Brain-Computer Interface,
Statistical Learning

Jong-Hwan Lee
Brain Signal Processing,
Real-Time fMRI, Machine Learning

Jee-Hyun Kwag
Neural Computation

Christian Wallraven
Psychophysics,
Cognitive Systems

Jae-Seok Park
Biomedical Imaging,
MRI, Brain Imaging

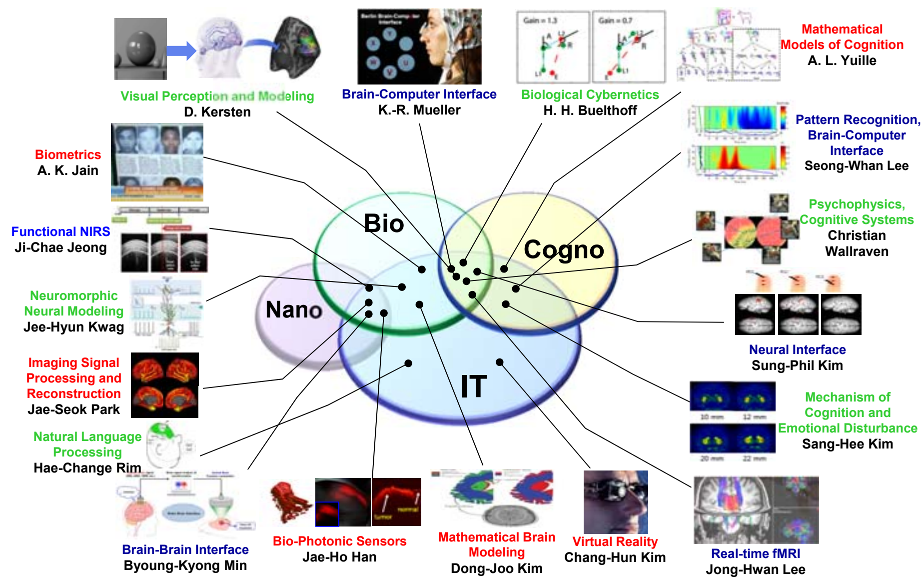
Jae-Ho Han
Bio-Photonic Sensors,
Micro-Endoscopic Imaging

Dong-Joo Kim
Mathematical Brain Modeling,
Functional Cerebral Monitoring

Byoung-Kyong Min
Brain-Brain Interface (EEG & Ultrasound),
Ultrasound-Mediated Neuro-Modulation

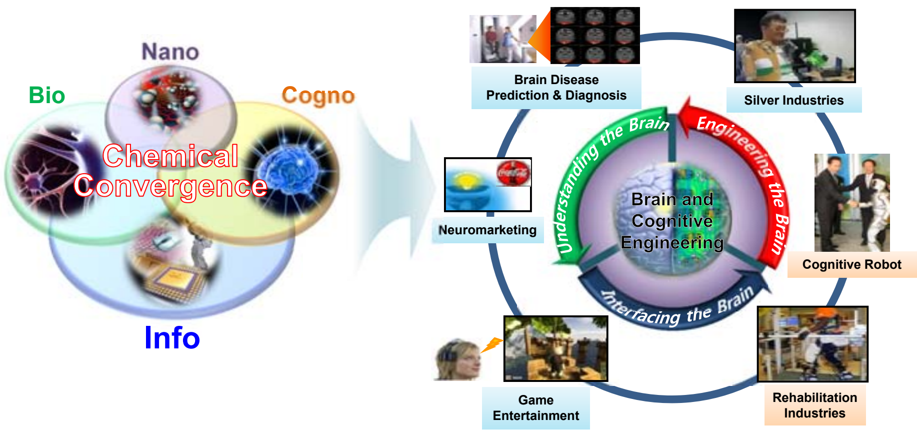
Multi-Disciplinary Research

Cognitive Brain Science　Brain-Computer Interface　Brain Imaging Engineering

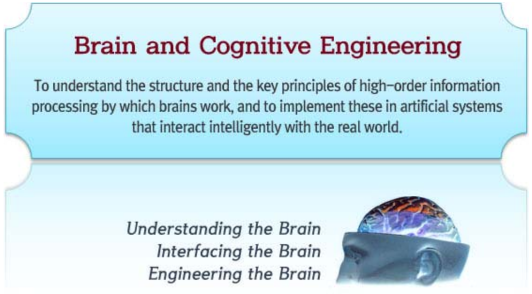


What is Brain and Cognitive Engineering?

To understand the structure and key principles of high-order information processing by which brain works and to implement these in artificial systems that interact intelligently with the real world

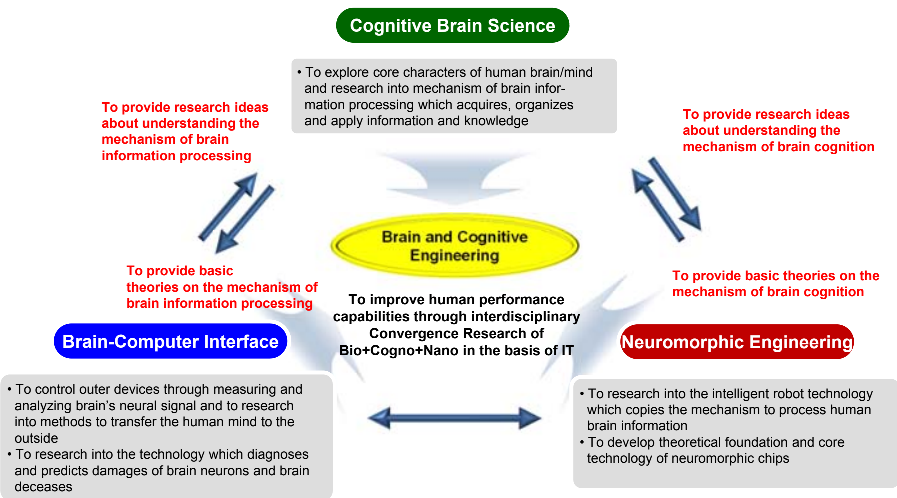


Research Objectives



- **To develop the human performance in terms of body, psychology and society which is the ultimate goal of the 21st science technology and to research into the technology of human-friendly Brain and Cognitive Engineering in order to perform human capabilities effectively**
- **To secure the core technology of Brain and Cognitive Engineering which is an undeveloped research field and to secure top research abilities worldwide through establishing the department of Brain and Cognitive Engineering in order to raising professional human resources**
- **By establishing R&D and R&E system through the department and the research institute of Brain and Cognitive Engineering, we create new study fields and raise professional human resources through scientific researches into respective fields and the exchange of interdisciplinary Convergence Technology**

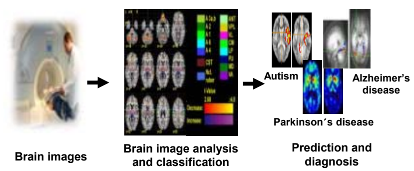
Research Contents



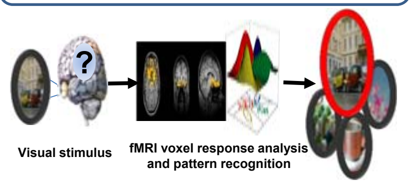
Expected Outcomes

- **Physical Assistance System Technology**
  - Natural control of physical assistance system and car safety system based on brain signal analysis

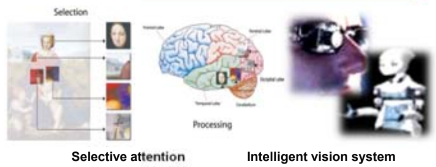
- **Brain Disease Prediction and Diagnosis**
  - Automatic detection of the brain area which may cause brain disorder and brain disease prediction



- **Mind-Reading Technology**
  - Reading out mental contents and psychological status from human brain activity



- **Artificial Vision System Technology**
  - Visual information processing in the brain such as selective attention applied to intelligent robots



Research Facilities (1/2)

- MAGNETOM Trio A Tim System 3 Tesla (Siemens, Ltd.)

- SynAmps II 32 Channels (NeuroScan, Inc.)
- g.USBamp 16 Channels (g.Tec, Inc.)

Research Facilities (2/2)

Magstim Rapid[2] (Transcranial Magnetic Stimulator) (The Magstim Co., Ltd.)

3dMDface System (3dMD, Inc.)

Fastrak 3D Tracker (Pohemus, Inc.)

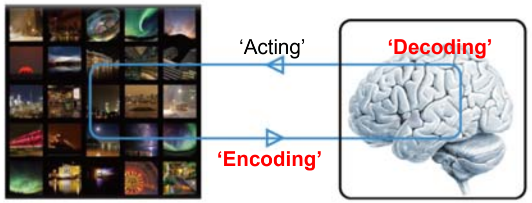
HAPTIC Omega 3 (Force Dimension, Inc.)

nVisor MX120 (HMD) (NVIS, Inc.)

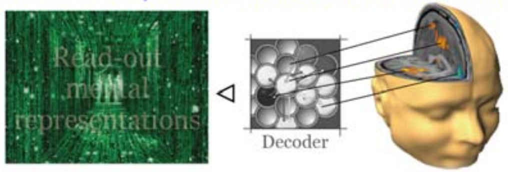
Brain Decoding

To interpret or understand behavioral response/stimulus/ psychological state by decoding the patterns of brain activities

Exogenous or endogenous stimuli are encoded and decoded in the brain



If we can decode the brain responses/activities, then we can read the mental states



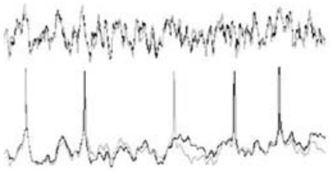
Applications of Brain Decoding

- Brain-Computer Interface (BCI)
  - Translation of human intentions into a technical control signal without using activity of muscles or peripheral nerves
- Brain disease prediction and diagnosis
  - Extracting patterns of mental diseases
  - Alzheimer, schizophrenia, depression, etc.
- Predicting mental states
  - e.g.) Looking at a face or a building?
    Listening to Chinese or Korean sentences?
- Lie detection
  - Looking right into the brain to track a lie

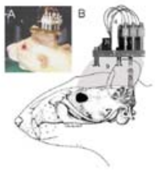
How to Measure Brain Activity? (1)

Invasive recordings from brains

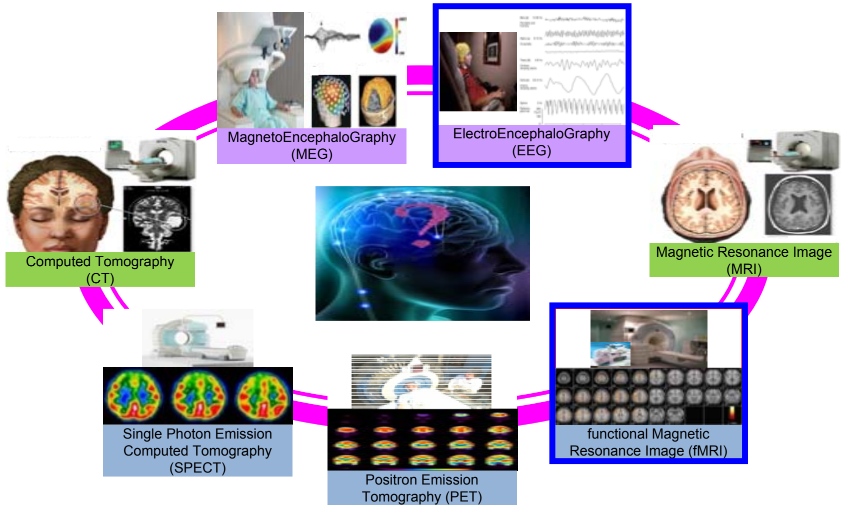
Single-unit



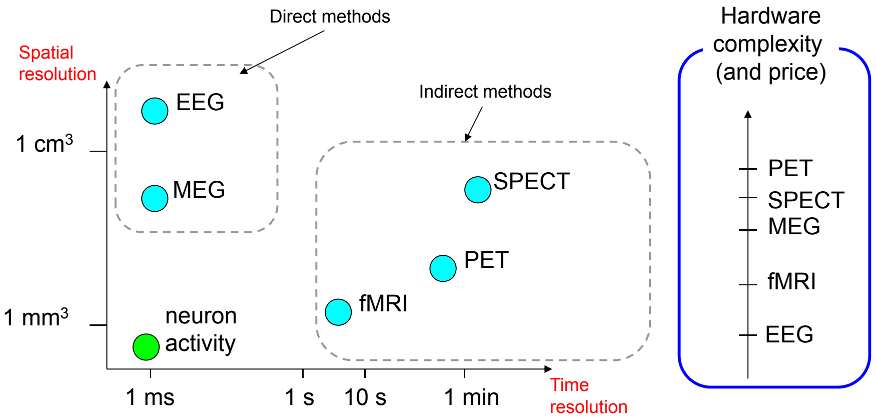
Multi-unit



How to Measure Brain Activity? (2)



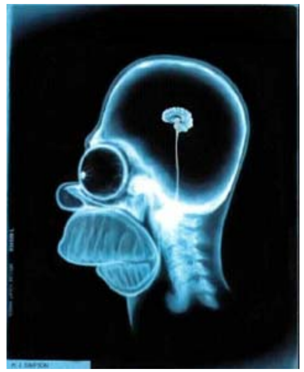
How to Measure Brain Activity? (3)



Functional MRI (fMRI)

MRI vs. fMRI

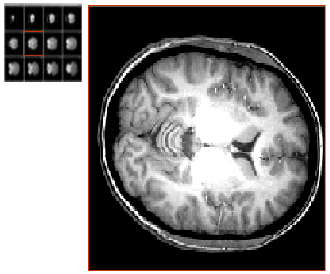
Magnetic Resonance Imaging (MRI) studies brain anatomy



Functional MRI (fMRI) studies brain function

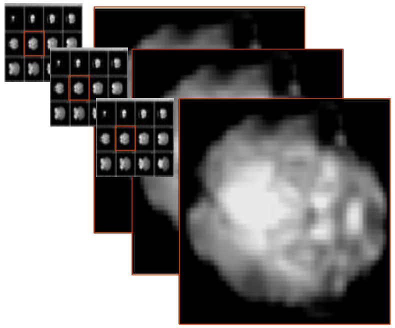
Functional MRI (fMRI) (1)

MRI: single volumetric dataset to study **brain structure**



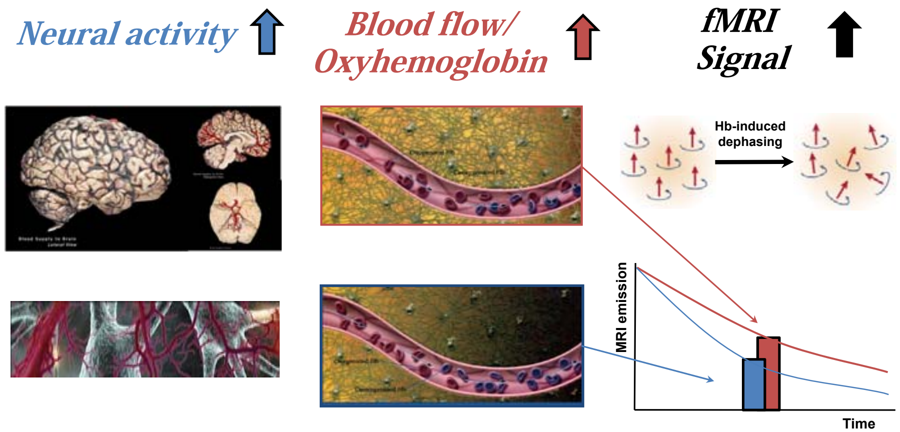
High resolution: $1mm^3$ voxels
(one image)

fMRI: volumetric **time-series**, e.g. acquire one volume every 2 sec for 5 min, to study **brain function** over time



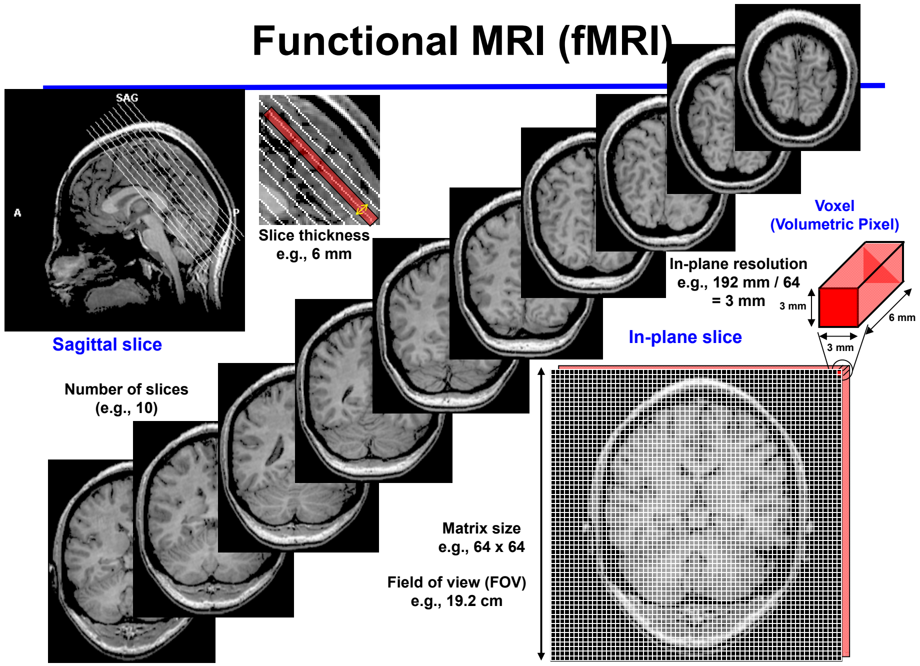
Low resolution: ~$3mm^3$ voxels
(many images)

Functional MRI (fMRI) (2)

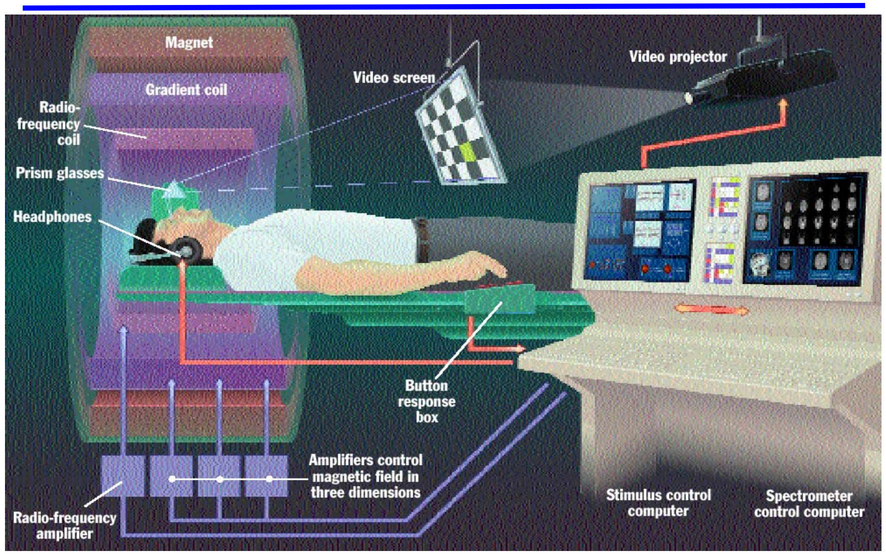


fMRI: **B**lood **O**xygenation **L**evel **D**ependent (**BOLD**) signal
indirect measure of neural activity

Functional MRI (fMRI)



fMRI Experimental Setup



Electrical Signal Recording

Neurons
- Individual nerve cells are connected to one another by dendrites and axons
- Its activity is carried out by small electric signals that travels from neuron to neuron as fast as 250 mph

Brain signals
- Generated by differences in electric potential carried by ions on the membrane of each neuron

Invasive

Implanted directly into the brain

Used to treat acquired blindness
- A single-array containing 68 electrodes
- Implanted onto visual cortex
- Succeeded in producing phosphenes, the sensation of seeing light

Partially Invasive

ElectroCorticoGraphy (ECoG)
Placed directly on the exposed surface of the brain to record electrical activity from the cerebral cortex

Non-Invasive

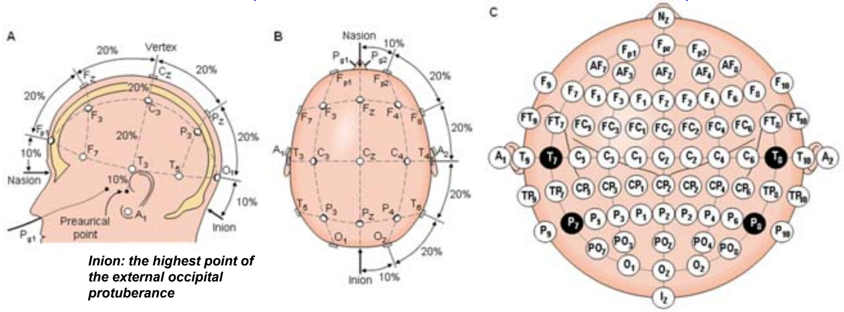
ElectroEncephaloGraphy (EEG)
From electrodes placed on the scalp

Much ← **Little**

Detailed information on the activity of single neurons

ElectroEncephaloGraphy (EEG) (1)

An internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG test or experiment

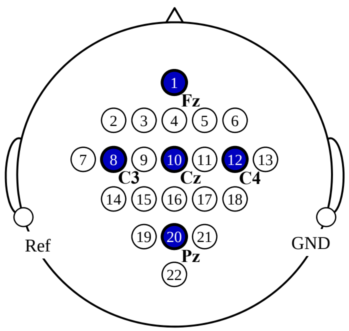


The **international 10-20 standard system** seen from (A) left and (B) above the head.
A=Ear lobe, C=central, T=temporal, P=parietal, F=frontal, Fp=frontal polar, O=occipital.
(C) Location and nomenclature of the intermediate 10% electrodes, as standardized by the American Electroencephalographic Society. (Source: http://www.bem.fi/book/13/13.htm#03)

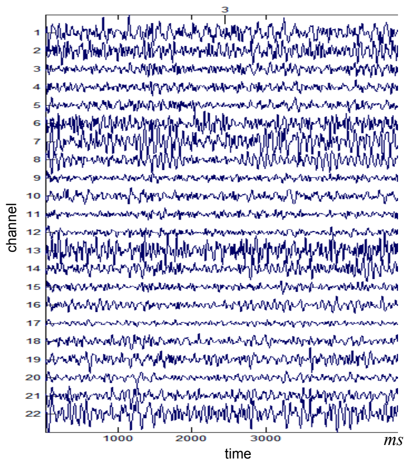
Ensures standardized reproducibility so that a subjects studies could be compared over time and subjects could be compared to each other

ElectroEncephaloGraphy (EEG) (2)

EEG is a multi-dimensional signal from multiple channels
(high temporal resolution)



22 channels



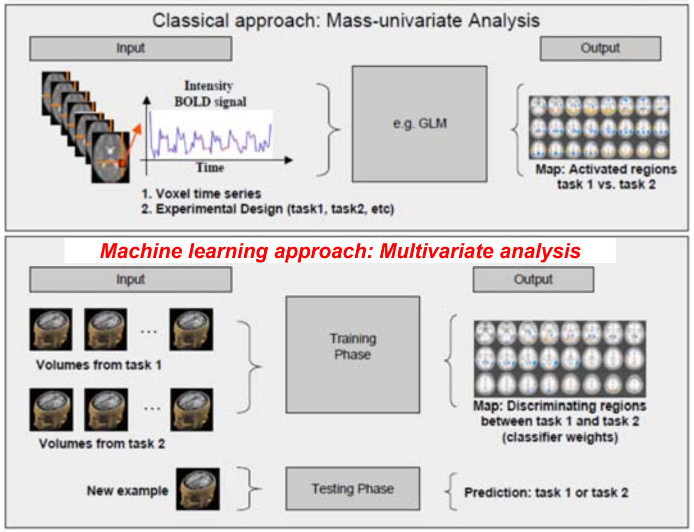
How to Decode Human Brain

Brain Decoding Approaches (1)

Machine learning techniques are now changing the way neuroimaging data are analyzed

- Address the problem of classifying the cognitive state of a subject based on the brain signal such as fMRI and EEG data
- Based on a training set, identify a distributed pattern of activation that discriminates two or more cognitive states and uses this pattern to make prediction for new data
- Mapping: brain signal → cognitive state

Brain Decoding Approaches (2)



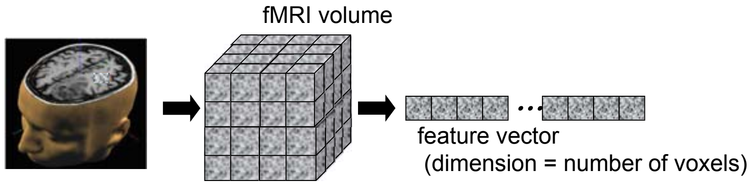
Source: J. Mourao-Miranda, IEEE-WBD, 2010

Why Machine Learning?

- Explore the multivariate nature of neuroimaging data
  - fMRI, EEG data are multivariate by nature
    - fMRI: each scan contains information about brain activity at thousands of measured locations (voxels)
    - EEG: each signal contains multiple electrodes (channels)
  - Most of the brain functions are distributed processes
    - involving a network of brain regions it seems advantageous to use the spatially distributed information contained in the data to give a better understanding of brain functions
- Can be used to make predictions for new examples
  - Enable clinical applications
    - Previously acquired data can be used to make a diagnosis or a prognosis for new subjects

Data Representations

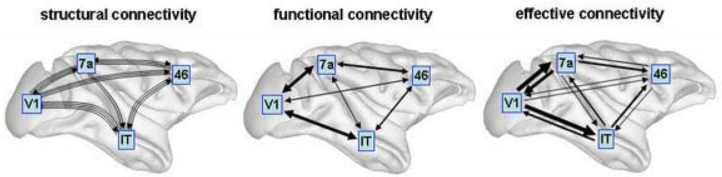
- Feature selection
  - High-dimensional time series data
    - fMRI: 15,000-20,000 voxels per image



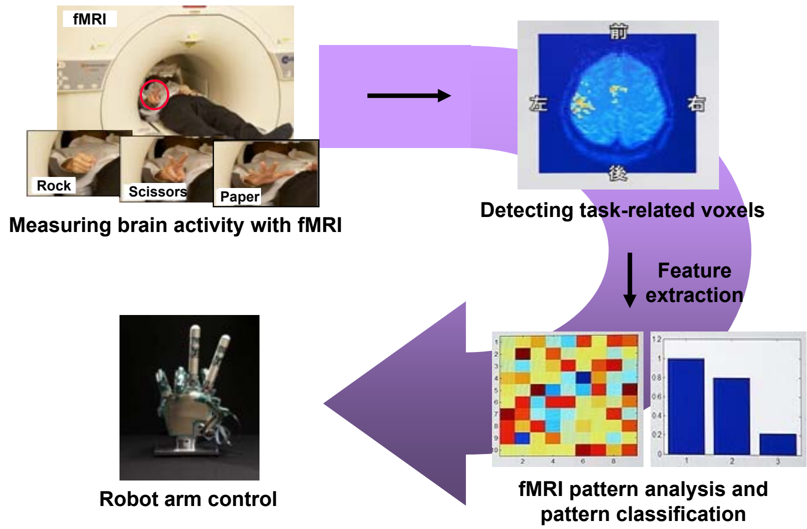
- Find a mathematical criteria to separate the data into **meaningful** components
  - Sparse coding representations or dimensionality reduction
    - Noise reduction, visualization, interpretability (component analysis), etc
    - Principal component analysis (PCA), Independent component analysis (ICA), Locally Linear Embedding (LLE), clustering algorithms (e.g., K-means, spectral clustering, etc.)

Classifiers for Brain Decoding

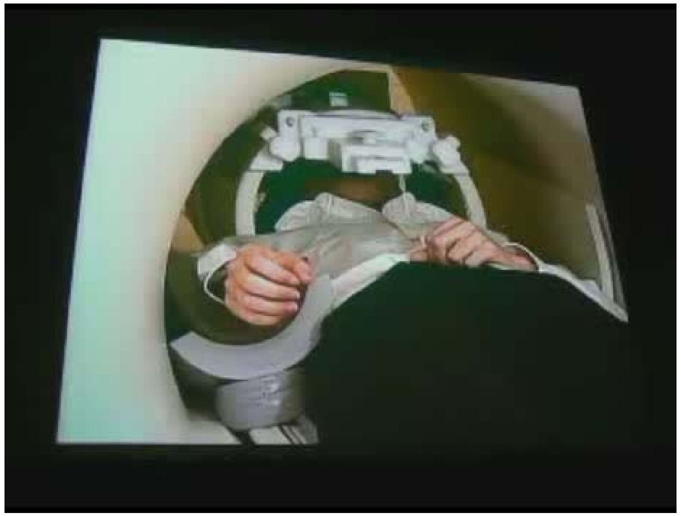
- Regularization schemes
  - Typically small number of examples (trials) compared with features (voxels): highly possible to be overfitted
- Functional/Effective connectivity among brain areas
  - Functional: statistical dependencies between regional time series
  - Effective: causal (directed) influences between neurons or neuronal populations



Robot Arm Control with fMRI Analysis (1)



Robot Arm Control with fMRI Analysis (2)



Visual Image Reconstruction from Human Brain Activity (1)

Development of a novel machine-learning techniques to decode fMRI signals for visual image reconstruction

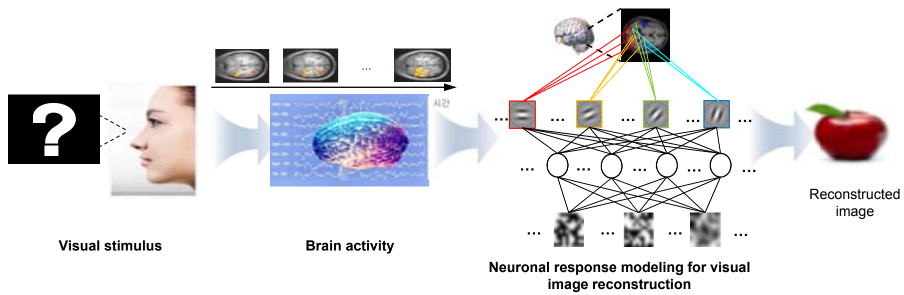
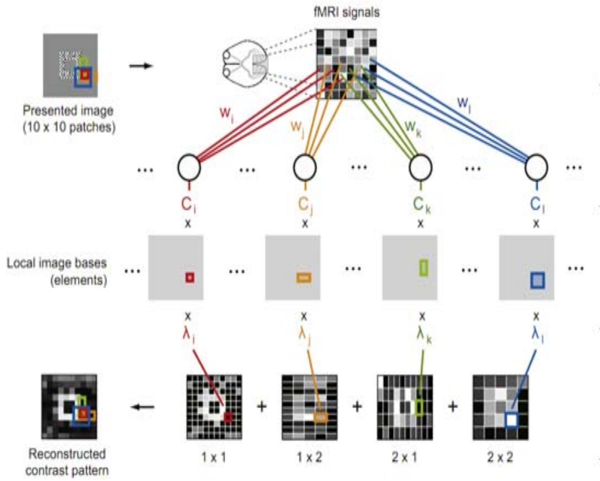


Illustration of visual image reconstruction from human brain activity

Visual Image Reconstruction from Human Brain Activity (2)

Y. Miyawaki, et al., Neuron, Vol. 60, December 2008.



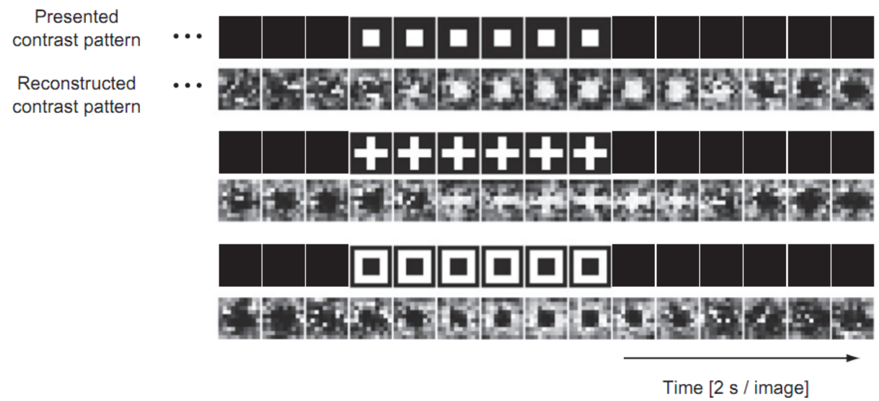
fMRI activity is measured while a contrast-defined 10x10 patch image is presented

Local decoders use linearly weighted multi-voxel fMRI signals to predict the contrasts of local image bases of multiple scales

Local image bases are multiplied by the predicted contrasts and linearly combined using coefficients to reconstruct images

Visual Image Reconstruction from Human Brain Activity (3)

- Visual image reconstruction from a single-volume fMRI
  - In this result, the hemodynamic response delay is not compensated



Brain-Computer Interface with Machine Learning

Movie Fiction: The Matrix

In the futuristic vision of the Wachowski brothers' movie trilogy "The Matrix," humans dive into a virtual world by connecting their brains directly to a computer…

Most movie viewers may consider direct interfaces with the nervous system as much of a fantasy as the movie's gravity-defying special effects. However, this very idea is very real.

The Matrix (1999)

Total Recall (1990)

Avatar (2010)

Brain-Computer Interface (BCI) (1)

Brown University, Nature, 2006

Brain-Computer Interface (BCI) (2)

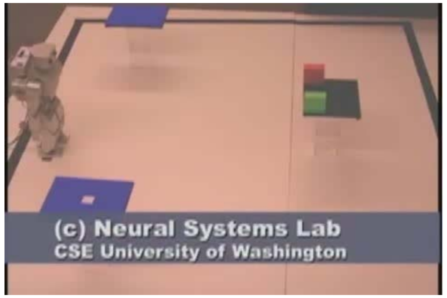
Monkeys control a robot arm with thoughts

- ✓ By analyzing the monkey's brain signals
- ✓ To pluck and eat a marshmallow

University of Pittsburgh, Nature, 2008

A human controls a robot with thoughts

- ✓ By analyzing the human's brain signals
- ✓ To move the red/green block to other place



University of Washington, 2006

Why BCI?

- **Moving closer to making some science fiction into reality**
  - **The power of modern computers grows alongside our understanding of the human brain**
- **Manipulating computers or machinery with nothing more than a thought**
  - **For severely disabled people: The most important technological breakthrough**

What is BCI?

Translation of human intentions into a technical control signal without using activity of muscles or peripheral nerves

Overview of an EEG-based BCI System

Challenges

- High signal variability intra- and inter-subjects
- Unknown underlying physics
- Linear or nonlinear model
- Man-computer learning dilemma

Expected Outcomes

- EEG-based virtual walking or game interface
- Controlling home appliances (Smart home)
- Driving a wheel-chair by thought

Signal Characteristic

Non-invasive EEG-based BCIs can be classified as "evoked" or "spontaneous"

Evoked BCI

- Also called Event-Related Potential
- Reflects the immediate automatic responses of the brain to some *external stimuli*
- Easy to pick up
- Only applicable to a limited range of tasks

Spontaneous BCI

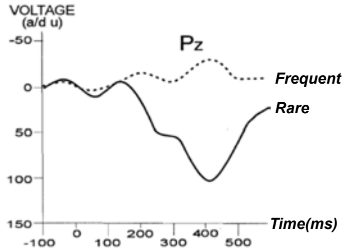
- Based on the analysis of EEG phenomena associated with various aspects of *brain function related mental tasks* carried out by the subject **at his/her own will**
- Intentional mental activity

Event-Related Potentials (ERP)

- Event-Related Potential
  - Electrocortical potentials that can be measured in the EEG before, during, or after a sensory, motor, or psychological event
  - *A fixed time delay to the external stimuli*
  - Their amplitude is usually much smaller than the ongoing spontaneous EEG activity
    - Because ERPs are more localized in the corresponding cortical areas
  - Averaged ERP
    - Used for the detection of ERPs
    - Composed of a series of large, biphasic waves, lasting a total of five hundred to thousand milliseconds
- P300
- SSVEP (Steady-State Visually Evoked Potential)

P300

P300 is a positive wave that occurs about 300 milliseconds after the onset of the target/rare (oddball) stimulus among a sequence.



- *Polarity (positive)*
- *Latency (>275 ms)*
- *Less frequent stimuli produce larger response*

e.g.) P300 Speller
- *6-by-6 matrix* containing characters and symbols
- Flashing each row and column for 100 ms in random order
- Instructing participants to focus to only one of the 36 cell
- In one sequence of 12 flashed, *the target will flash only twice*
  - A rare event compared to the 10 flashes

Ecole Polytechnique Federale de Lausanne(EPFL), Switzerland

Source: Wolpaw, et al., 2002

SSVEP

Steady-State Visually Evoked Potential(SSVEP)

natural responses to visual stimulation at specific frequencies

When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, the brain generates electrical activity at the same (or multiples of) frequency of the visual stimulus

Tsinghua university BCI Group, 2008

- Each square in the upper panel flashes at an individual frequency.
- By spectral analysis of the EEG the regarded square can be detected from the predefined-length windows.

Spontaneous BCI

- Spontaneous BCI
  - Based on the analysis of *EEG phenomena* associated with various aspects of *brain function related to mental tasks* carried out by the subject at his/her own will
- Two kinds of spontaneous or endogenous brain signals
  - SCP (Slow Cortical Potentials) – temporal domain
  - Rhythmic activity – frequency domain
    - μ(8~12Hz) and β(13~28Hz) rhythms
    - ERD (Event-Related Desynchronization)
    - ERS (Event-Related Synchronization)

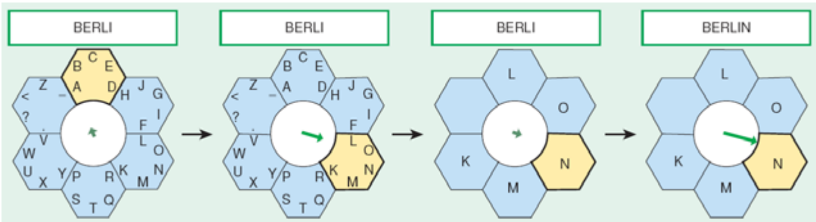
Rhythmic Activity (Motor Imagery)

Local variations of EEG rhythms, μ(8~12Hz) and β(13~28Hz), in the frequency domain

The mental typewriter Hex-o-spell

Two-step procedure for letter selection
- *Right-hand movement - turning the arrow in clockwise*
- *Right-foot movement - extending the arrow*

Speed
- *Between 2.3 and 5 chars/min for one subject*
- *Between 4.6 and 8.3 chars/min for the other subject*



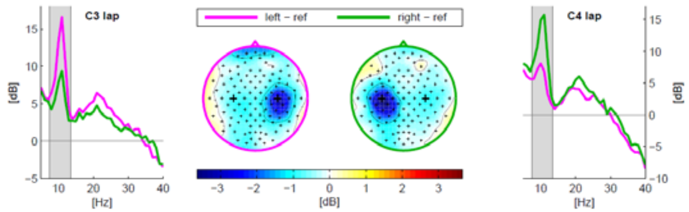
Source: K.-R. Muller and B. Blankertz, 2006

Introduction to Ongoing Researches in CVPR Lab.

1. Brain-Computer Interfaces

Imagination of Body-Part Movement

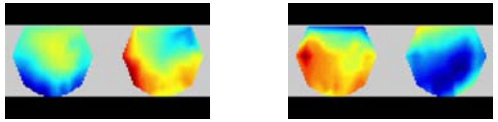
- Idle rhythms with no activity of physical or imagined limbs movement
  - Large population of neurons in cortex are ring in rhythmical synchrony
- Event-Related (De)Synchronization (ERD/ERS)
  - Attenuation of the idle rhythms in μ (8-13Hz) and β (14-30Hz)
  - Enhancement of the rhythmic activity (viewed as rebound of ERD)
  - Predominantly contralateral to the moved limb



Modulation of sensorimotor rhythms in motion imagery [Blankertz et al., 2008]

Background

- Spectral filtering
  - Advisable to reduce the frequency content of the EEG signal to some frequency band of interest
    - ERD/ERS-complex can be found predominantly in the μ and β-band
    - However, highly variable across subjects and across even trials for the same subject



EEG features in different frequency bands: (left) 5-30Hz, (right) 10-14Hz

- Spatial filtering
  - To find the signal that originates at a specific scalp location
    - Every EEG electrode measures a superposition of signals derived from various sources in the brain
    - To take a linear combination of signals recorded over EEG channels and extract only the component that we are interested in

Prevalent Steps in Motor Imagery Classification

Spectral filtering: $\mathbf{Z} = h \otimes \mathbf{X}$ $\quad$ ($\mathbf{X}$: single trial EEGs, h: spectral filter)

Spatial filtering: $\mathbf{Y} = \mathbf{W}^T \mathbf{Z}$ $\quad$ ($\mathbf{W}$: spatial filter)

Feature extraction: $\mathbf{F} = \log(\mathrm{var}(\mathbf{Y}))$ $\quad$ ($\mathbf{F}$: feature vector)

- No general method that analytically finds the optimal frequency band
  - Either selected manually based on a visual inspection or unspecifically set to a broadband
- Spatial filter learning (Common Spatial Pattern: CSP [RMGP00]) on bandpass-filtered signals
  - Dependent on the operational frequency band

Learn spatio-spectral filters simultaneously in a unified framework

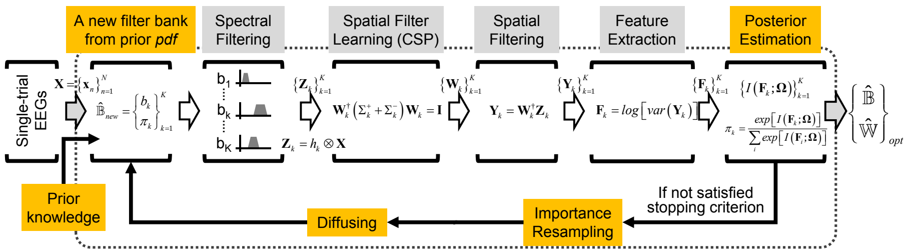
Bayesian Spatio-Spectral Filter Optimization

- Represent a frequency band as a random vector **B**
  - Statistical viewpoint: optimizing the spatio-spectral filter as probability density estimation function (*pdf*) and exploitation
- Estimate the unknown posterior *pdf* $p(\mathbf{B}|\mathbf{X};\boldsymbol{\Omega})$
  - Indicates the relative probability of the single trial EEGs **X** being correctly classified into **Ω** by **B**-bandpass filtering along with the ensuing computational processes
  - No functional assumption about the density
- Learn the spatial filter **W** in each of the estimated optimal frequency band individually

H.-I. Suk and S.-W. Lee, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 2012 (Accepted)

Proposed Bayesian Framework

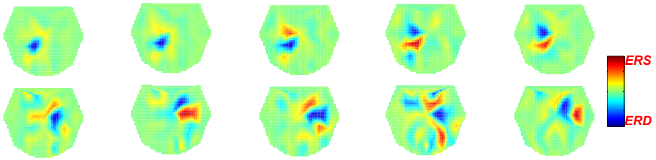
Discriminative feature extraction by means of the spatio-spectral filters optimization in a probabilistic Bayesian framework



A schematic diagram of the proposed method for class-discriminative feature extraction by means of spatio-spectral filter optimization in a probabilistic Bayesian framework

Experimental Results

- Publicly available datasets
  - Technische Universität Berlin Dataset
  - BCI Competition III Dataset-IVa, BCI Competition IV Dataset-IIa
- Competing state-of-the-art methods in the literature
  - CSP (Common Spatial Pattern) [RMGP00]
  - CSSP (Common Spatio-Spectral Pattern) [LBCM05]
  - FBCSP (Filter Bank CSP) [ACZG08]
  - OSSFN (Optimal Spatio-Spectral Filter Network) [ZCA+11]



CSP CSSP FBCSP OSSFN **Proposed**

Topography maps of the learned spatial filter for Technische Universität Berlin Dataset

The proposed method has found spatial filters consistent with the neurophysiological knowledge

The proposed method is statistically significant (>95.5% confidence level) compared to the state-of-the-art methods in the literature

2. Neuro-Driving

Emergency Situations in Driving

Unexpected pedestrian appearance

Sudden braking of the leading vehicle

Statistics on the Traffic Accidents Caused by Human Factors

(단위 : 건, 명, %)

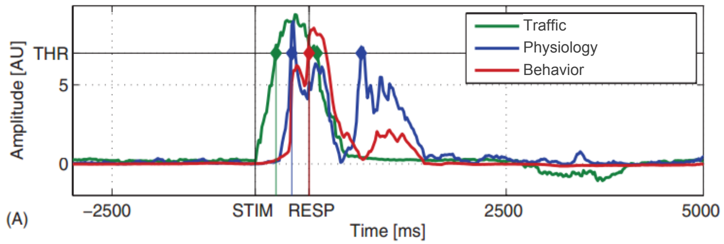
인적요인 \ 구분	발생건수		사망자수			부상자	
		구성비		구성비	치사율		구성비
계	236,417	100.0	10,729	100.0	4.5	241,691	100.0
전방주시태만	160,784	68.0	8,011	74.7	5.0	162,800	67.4
환경요인에의한발견지연[1)]	1,798	0.8	162	1.5	9.0	1,796	0.7
심리적요인에의한판단잘못[2)]	6,823	2.9	202	1.9	3.0	7,218	3.0
고의적운전행태[3)]	243	0.1	5	0.0	2.1	283	0.1
차량조작잘못	2,267	1.0	87	0.8	3.8	2,799	1.2
심신건강상태불량[4)]	7,985	3.4	581	5.4	7.3	9,175	3.8
기타,불명	56,517	23.9	1,681	15.7	3.0	57,620	23.8

[Source: Traffic Accident Analysis Systems (TAAS), 2011]

Driver's psychological abnormal condition (drowsiness, overwork, etc.) and freezing behavior is classified as main factors to traffic accidents

Freezing behavior: a phenomenon of not making any reaction to a sudden stimulus (or activation of a dangerous situation) because of the confusedness or fearfulness

Brain Signal Analysis based Response vs. Behavioral Response

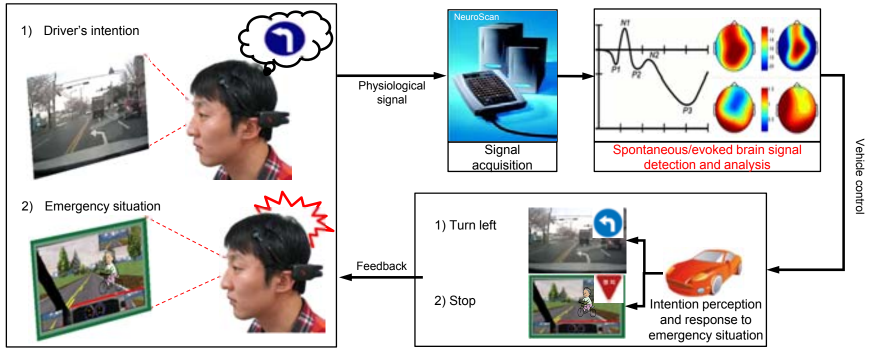


[Source: Haufe et al., Journal of Neural Engineering, 2011]

Based on the neurophysiological study, the physiological response-based braking is faster than the normal behavior response-based one (3.66m in 100km/h)

Research Outline

Development of a smart driving assistant technique that can perceive driver's intention and detect an emergency situation based on spontaneous and evoked brain signals, respectively



Automatic emergency situation perception based on brain activity analysis

Research Contents

Development of a smart driving assistant technique that can perceive driver's intention and detect an emergency situation based on spontaneous and evoked brain signals, respectively

Emergency situation perception
with brain signal analysis

- Construction of Spontaneous/evoked brain signal database with 30 subjects
- Human intention recognition rate for the vehicle driving control : more than 90%
- Accident avoid rate based on emergency situation recognition: more than 90%

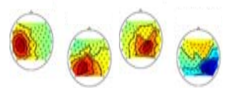
• Control commands: turn-left, turn-right, stop, start
• Emergency situations: unexpected obstacle/pedestrian appearance, sudden braking of leading vehicle
• Intention recognition rate (%) = 100×(# of correctly recognized intentions/total # of intentions)
• Accident avoidance rate (%) = 100×(# of correctly detected emergency situations/total # of emergence situations)

Testbed construction of driving environment with Unity 3D

- Construction of a brain signals database and of a testbed with Unity 3D
- Experimental paradigm design for spontaneous/evoked brain signal detection

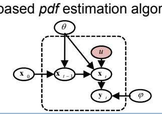
Spontaneous/evoked brain signals detection during driving

- Development of a spectrum-based brain signal analysis algorithm with for perceiving abnormal states
- Physical/psychological correlation analysis based on a temporal-spatial-spectral feature map



Development of a probabilistic framework for spontaneous/evoked brain signals analysis

- Development of a hierarchical Bayesian network reflecting the correlation among feature vectors
- Development of a sampling-based *pdf* estimation algorithm



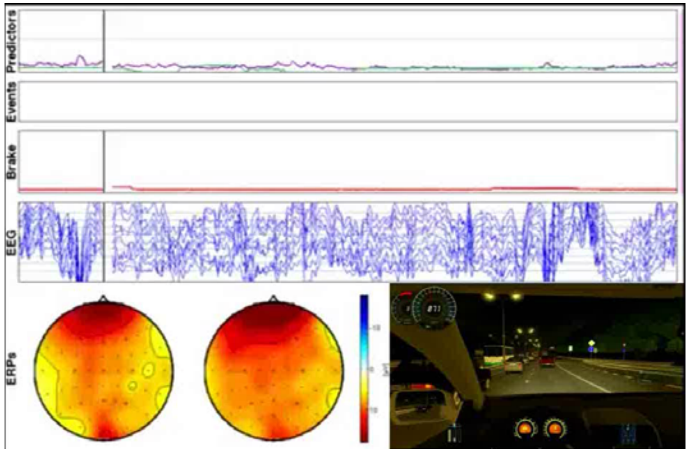
Driving Simulation Environment with Unity 3D

Building a city

Sudden stop of the leading vehicle

Driving over the centerline

An Example of the Neuro-Driving Prototype

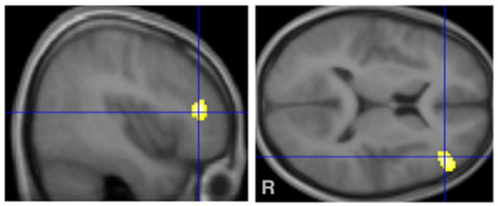


3. EEG-based Person Authentication

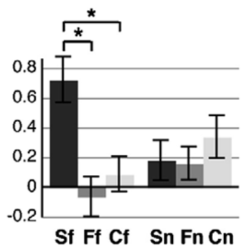
fMRI Study on Visual Self-Representation

Self-face can be a representative stimulus for visual self-representation

- Right inferior frontal, precentral, supramarginal, and bilateral ventral occipito-temporal cortices are highly responsive to self-face images



Right inferior frontal gyrus

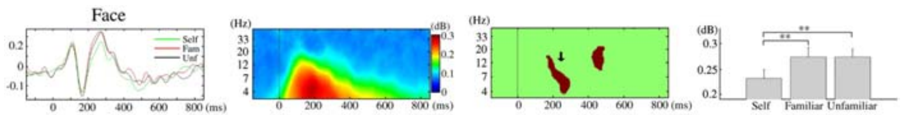


Self-specific activation as identified by self-friend [Sugiura et al., 2008]
(S: him/herself, F: friend, C: (Control) unfamiliar, f: face, n: name)

It supports that blood-oxygen-level dependence (BOLD) responses are possible evidence of face-specific visual self representation

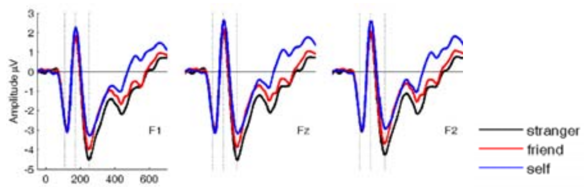
EEG Study on Visual Self-Representation

A brain response to one's own face was markedly different from that to familiar/unfamiliar non-self-faces



Averaged event-related IC activity | Mean ERSP across Self, Familiar, Unfamiliar | Statistical differences across 3 conditions | Mean and standard error

Independent Component (IC) activities in medial frontal (MF) cluster [Miyakoshi et al., 2010]

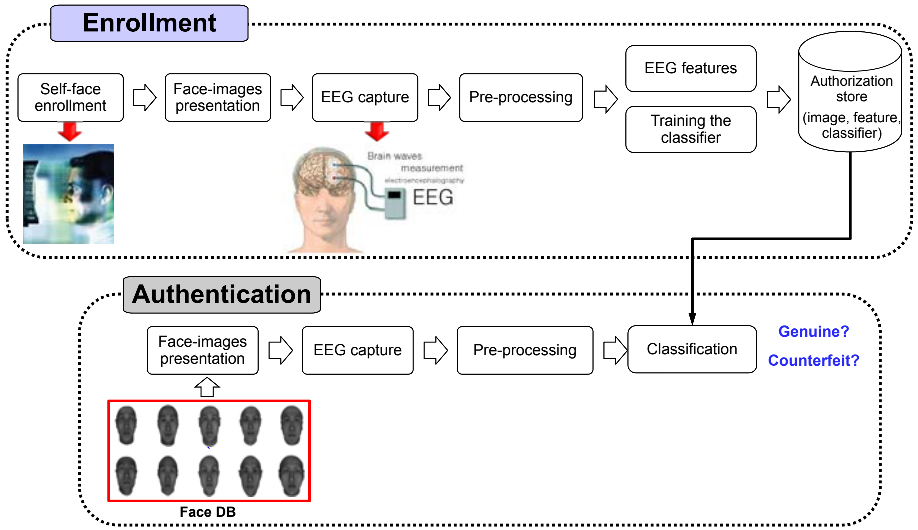


Event-related potentials for self, friend and stranger faces for the 3 fronto-central channels [Keyes et al., 2010]

EEG-based Person Authentication (1/2)

- A novel stimulus representation paradigm for EEG-based person authentication using self- and non-self-face images as stimuli
  - A clear evidence of generating a unique subject-specific brain-wave pattern from studies in psychology and neurophysiology [Uddin et al., 2005, Keyes et al., 2010]
  - Robust paradigm in terms of the universality, distinctiveness, permanence, collectability and uniqueness
- It is believed that the brain signal evoked by the face-specific self representation is greatly qualified as a biometric

EEG-based Person Authentication (2/2)

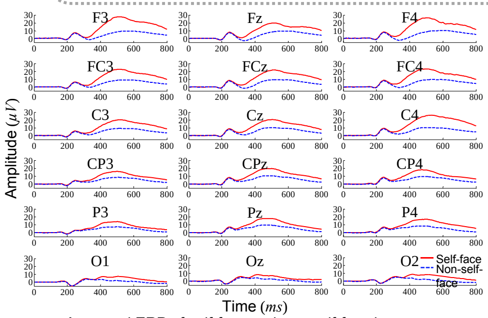


Overview of the proposed framework

Experimental Results

Experimental Results

- Self-collected dataset
  - 9 healthy subjects (27.3±1.9 years, males, right-handed)
  - 3dMD face system for face images acquisition
  - Neuroscan SynAmps2, BCI2000 for EEG recording (sampling rate: 250Hz)
  - 2 sessions conducted on different days (2 runs/session, 50 trials/run)



Averaged ERP of self-face and non-self-face images

The ERP for a self-face stimulus is clearly distinguished from that for a non-self-face stimulus

Performance of the proposed method

	Accuracy (%)	FAR (%)	FRR (%)
Subject 1	84.5	18.1	13.1
Subject 2	94.9	4.7	5.6
Subject 3	93.7	7.7	5.0
Subject 4	86.6	10.2	16.6
Subject 5	80.6	19.9	19.1
Subject 6	95.3	4.7	4.7
Mean	**89.3**	**10.9**	**10.7**

FAR: False Acceptance Rate
FRR: False Rejection Rate

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Thank you for your attention