Practical Applications of Wearable EEG

Tzyy-Ping (TP) Jung

1Swartz Center for Computational Neuroscience and
2Center for Advanced Neurological Engineering
3Department of Bioengineering
UC San Diego, La Jolla, CA, USA

4Department of Computer Science
5Dept of Electrical Engineering
6Dept of Computer Science & Engineering
National Yang Ming Chiao Tung University, Hsinchu, Taiwan

7College of Education,
National Tsing Hua University
Hsinchu, Taiwan

8School of Precision Instrument and Optoelectronic Engineering
Tianjin University, Tianjin, China

Zhejiang University (浙江大学)
University of Macau (澳门大学)
Harbin Institute of Technology ( 哈工大)
University of Technology Sydney, Australia (雪梨科技大學)
East China University of Science and Technology (华东理工大学)
Yanshan University (燕山大学)

Huazhong University of Science and Technology (华中科技大学)
Chinese Academy of Sciences (中国科学院半导体所)
Tsinghua University (清华大学)
National Taipei University of Nursing and Health Sciences (國立臺北護理健康大學)
Outline

- Challenges in Real-World EEG
- Sample applications of wearable EEG
Challenges in Real-World Neuroimaging

- We lack new sensors and technologies to measure high-quality neural, physiological, behavioral, and contextual data in real-world environments.

- We need advanced signal-processing and machine-learning algorithms to jointly analyze multi-modal data.
Setting up an EEG Experiment is Laborious and Time-consuming
Non-prep EEG Sensors and Systems

Dry and non-prep EEG sensors

Wearable EEG Headgears

Cognionics

High-density (64-chan) EEG Cap
Wireless EEG Systems on the Market

He et al., under review.
ERP in a Well-controlled Laboratory

Laboratory Research

Mobile Brain/Body Imaging (MoBI)

Laboratory Research

Real-world Neuroimaging

Typical EEG experiment

Challenges in Real-World Neuroimaging

☑️ New sensors and technologies to measure high-quality neural, physiological, behavioral, and contextual data in real-world environments.

☐ Advanced signal-processing and machine-learning algorithms to jointly analyze multi-modal data.
Difficulties in Observing Distributed EEG dynamics

Scalp EEG signals appear to be noisy because they are a mixture of signals generated in many brain areas.
Biomedical Data Processing

EEG Acquisition

Pre-processing
Artefact Removal Sampling Filter

Feature Extraction

Power Spectral Connectivity

Neural Networks

Machine Learning
Train Test
Classifier Regression

CNN and GAN

RNN and LSTM

Transfer Learning

Independent Component Analysis

Car Kit Demonstration
March 8, 2005

Courtesy of SoftMax, Inc
Off-line Analysis and Visualization of EEG Source Dynamics

EEGLab Toolbox

EEGLAB – An Open Source Environment for Electrophysiological Research

Over 250,000+ downloads over the past 15 years!

Over 11,000 citations

EEGLab Toolbox

SLORETA

Patch-based SBL

EEGLab Toolbox

Source Information Flow Toolbox (SIFT)

Tim Mullen

BCILab Toolbox

Arnaud Delorme

Zeynep Akalin Acar

Christian Kothe

Neuroelectromagnetic Inverse Source Localization Toolbox

Scalp map

sLORETA

BCILab Toolbox
Real-time Data Processing Pipeline

- Pre-processing: Re-referencing, Filtering, Resampling, Artifact rejection and imputation (BCILAB)
- Source Identification: cLORETA (cortically constrained; adaptive Bayesian updates), CSD integration over ROIs
- Model Fitting: Sparse Adaptive Vector Autoregressive Modeling, Stability and Whiteness tests
- Time-Frequency Dynamics: Spectral and Coherence Estimation, Multivariate Granger Causality, Graph metrics computation
- Dimensionality Reduction, Classification, Cognitive State Identification

Mullen et al., Best Technical Poster of International BCI Meeting, Asilomar, CA, 2013.
Mullen et al., IEEE TBME, 2015.
UCSD Chancellor’s Dissertation Award, 2015.
Outline

- Challenges in Real-World EEG
- Sample applications of wearable EEG
Global BCI Market Research Report

• Silicon Valley Live (service number: guigumitanv), scientists at the Brain Science Center of Harvard University, and industry experts jointly published an analysis of the brain-computer interface industry in China and the United States in 2017. The article described the technical aspects of BCI, summarized the past, present and future of BCI, and discussed trends in the commercialization of BCIs.

• “硅谷 Live（服务号：guigumitanv）联合哈佛大学脑科学中心科学家及行业专家学者，共同打造中美首份脑机接口行业分析长文，深度解构脑机接口领域技术路线，描绘脑机接口商业化趋势及学科地图，预见前所未见。”

Source：硅谷密探
Estimated BCI Markets

- BCI for ADHD: $46B
- Brain monitoring: $12B
- EEG/EMG equipment: $2.5B
- Education learning: $250B
- Gaming: $120B
A Sample Multi-modal Neuroimaging Study in Science Learning

Hsiao-Ching She, Chih-Ping Liang, Li-Yu Huang, Wen-Chi Chou, Sheng-Chang Chen, Ming-Hua Chuang, Jiun-Yu Wu, Jie-Li Tsai, and Tzyy-Ping Jung

National Chiao Tung University and UC San Diego

Science Learning

Participants N = 63 (undergraduate students)

Experimental procedure

A Multi-modal Approach to Study Science Learning

$N = 63$
(undergraduate students)

## Fixation Durations Predicts Students’ Performance

<table>
<thead>
<tr>
<th>Covariate</th>
<th>B (^a)</th>
<th>SE</th>
<th>(p)</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.099</td>
<td>0.218</td>
<td>0.650</td>
<td>-0.3</td>
</tr>
<tr>
<td>First 1 fixation point</td>
<td>-0.023</td>
<td>0.053</td>
<td>0.668</td>
<td>-0.1</td>
</tr>
<tr>
<td>First 2 fixation point</td>
<td>0.036</td>
<td>0.050</td>
<td>0.474</td>
<td>-0.0</td>
</tr>
<tr>
<td>First 3 fixation point</td>
<td>0.021</td>
<td>0.044</td>
<td>0.631</td>
<td>-0.0</td>
</tr>
<tr>
<td>First 4 fixation point</td>
<td>0.027</td>
<td>0.045</td>
<td>0.539</td>
<td>-0.0</td>
</tr>
<tr>
<td>First 5 fixation point</td>
<td>0.116***</td>
<td>0.029</td>
<td>0.000</td>
<td>0.0t</td>
</tr>
</tbody>
</table>

The odds of students’ providing accurate responses \((e^{0.116} = 1.123)\) increased by **12.3%** for every 100 ms increase at the 5th fixation point.
Fixation-related Spectral Perturbations of the Frontal-midline Cluster

Multi-modal Neuroimaging: From Lab to Classroom

Li-Wei Ko, Oleksii Komarov, W. David Hairston, Tzyy-Ping Jung, Chin-Teng Lin

National Chiao Tung University, UC San Diego
US Army Research Lab
A Wearable Daily Sampling System (WDSS)

1. Objective measurements

The ReadiBand \textit{objectively} measures sleep quality

<table>
<thead>
<tr>
<th>Fatigue Group</th>
<th>Effectiveness Score</th>
<th>Reduced Reaction Time</th>
<th>Blood Alcohol Equivalence (BAC %)</th>
<th>Risk of Accident/Serious Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>90-100%</td>
<td>5%</td>
<td>0.00%</td>
<td>Very Low</td>
</tr>
<tr>
<td>Reduced</td>
<td>80-90%</td>
<td>18%</td>
<td>0.06%</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>70-80%</td>
<td>34%</td>
<td>0.05%</td>
<td>Elevated</td>
</tr>
<tr>
<td>High Risk</td>
<td>60-70%</td>
<td>55%</td>
<td>&gt; 0.06%</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>0-60%</td>
<td>100%</td>
<td>&gt; 0.11%</td>
<td>Very High</td>
</tr>
</tbody>
</table>

2. Subjective measurements

\textit{Subjective} estimates of fatigue and stress are logged on a smartphone

- Karolinska Sleepiness Scale (KSS, scale 1-9)
- Fatigue Visual Analog Scale (FVAS, scale 0-100)
- Pittsburgh Sleep Diary (PSD)
- Stress Visual Analog Scale (SVAS, scale 0-100)
- Depression Anxiety Stress Scales (DASS-21)
A Longitudinal Study of the Effects of Stress on Neurophysiology and Task Performance

• This pilot study has collected 197 sessions of EEG/behavioral data from 26 (18+8) students over two 20-week semesters.

• Students’ resting EEG data were collected under the eyes-open condition for 5 minutes, followed by a DASS21 test before classes.

• Classroom stressors: examination (midterm & final), quiz, teacher asked subjects questions, teacher monitored the subjects to answer the exam.

Ko et. al., Frontiers in Human Neuroscience, 2017.
Correlations between Daily Sampling Measurements

Resting-state EEG spectral characteristics under stress

A. Depression

B. Anxiety

C. Stress

Classroom Activity

- Stimulus onset
- Response onset
- End of the trial

Timeline, s

EEG

Video monitoring

Stimulus

Response
Mental Fatigue in the Classroom

Spectral Differences (Inattentive - alert)

An increase in the normalized RT in the visual attention task is associated with

- delta and theta powers in the occipital region.
- beta power in the temporal and occipital regions.
- delta, theta and alpha powers in the frontal region.

Translating a BCI from Bench to Clinic

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

UC San Diego, Duke University, and nGoggle
Steady-state visual evoked potentials (SSVEP)

SSVEP are signals that are natural responses to visual stimulation at specific frequencies.
A High-Speed BCI Speller

High ITR $\sim 325.33 \pm 38.17$ bits/min (75 letters/min)
Nakanishi et al., IEEE TNSRE, 2018.
Glaucoma

- Glaucoma, once thought of as a single disease, is a broad term for a group of certain pattern damage to the optic nerve.
- Glaucoma is a leading cause of irreversible blindness.
- Vision loss can occur with normal or even below-normal intraocular pressure.
- In 2020, about 80 million people have glaucoma worldwide.
- At least 50% of people with glaucoma do not know they are affected.

Source: United Nations
Assessing Visual-Field Deficits

Standard Automated Perimetry (SAP) for Glaucoma Diagnosis
Assessing Visual-Field Deficits

Main idea:

The smartphone renders mfSSVEP stimuli and measures EEG/EOG data from the on-board bio-amplifiers.
Results from mfSSVEP and Standard Perimetry of Glaucomatous and Health Eyes.

## A Comparison between SAP and BCI Perimetry

<table>
<thead>
<tr>
<th></th>
<th>Standard Automated Perimetry (SAP)</th>
<th>BCI-based Visual-field Assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Equipment Cost</strong></td>
<td>$30,000 – $50,000</td>
<td>$500</td>
</tr>
<tr>
<td><strong>Operation Cost</strong></td>
<td>$100 / test</td>
<td>$30 / month</td>
</tr>
<tr>
<td><strong>Test Procedures</strong></td>
<td>Cumbersome: 30mins, Technicians</td>
<td>Simple: 10mins, DIY</td>
</tr>
<tr>
<td><strong>Test Sites</strong></td>
<td>Hospitals / Clinics, Appointments</td>
<td>Home, Free schedules</td>
</tr>
<tr>
<td><strong>Test Frequency</strong></td>
<td>Avg. once / 3‒6 months</td>
<td>Avg. once / day</td>
</tr>
<tr>
<td><strong>Test Reliability</strong></td>
<td>Subjective &amp; few data points</td>
<td>Objective &amp; many data points</td>
</tr>
</tbody>
</table>
Well-controlled EEG Lab → a VR+EEG HMD

Setup for a typical EEG experiment

Advantages:
• Integrate and synchronize visual/auditory stimulations and bio-signal collection.
• Miniaturized System-on-Modular for data collection, real-time signal processing and machine-learning classification
• Easy to set a standard operating procedure (SOP) and automation
• Cost-efficiency, portability, and scalability
Summary

➢ Challenges in Real-World EEG

• New sensors and technologies to measure high-quality neural, physiological, behavioral, and contextual data in real-world environments.

• Advanced signal-processing and machine-learning algorithms to jointly analyze multi-modal data.

➢ Sample applications of wearable EEG

• Multi-modal approach to study science of learning

• Multi-modal Neuroimaging from Lab to Classroom

• Translate a Brain-Computer Interface from bench to clinic
Acknowledgements

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