EEG in the Wild

Neurotechnology for 24/7 brain state monitoring
Quick intro

Physicist... a long, long time ago ...
Head of Section for Cognitive Systems, DTU Compute, Technical University of Denmark

Invented the **ensemble method** with Peter Salamon... (IEEE PAMI, 1990).

Since mid-90s work on systems neuroscience /neuroimaging:
**First papers on mind reading** (*PET*, 1994) and (*fMRI*, 1997)

Discovered “**Variance inflation**” (NIPS 2001) and fixed it for kPCA (JMLR, 2011) and SVMs (PRL, 2013).
Recovering structure from undersampling biases due to small samples in high-dimensional spaces

AISTATS 2016: “**Dreaming more data... **”
On deep learning with limited sample sizes

Promoting “**EEG in the wild**”:

**The Smartphone Brain Scanner**
New Scientist Nov 2011: “**Now you can hold your brain in the palm of your hand**”
How did you sleep last night?

Science, social engineering and bio-medical innovation - all rooted in predictive, causal understanding of human behavior - “the physics of behavior”

Predictive modeling is realized by quantitative measures and active machine learning

.. we have only limited quantitative self insight...

**self-report is of limited use** in science, engineering, bio-medicine...
Cognitive science in the wild

Why in the wild?
A necessary science of the individual ...

**Human predictability** - power laws ... need individual’s data to predict

Brain is different in the wild ... even in lab motion matters: ‘...most neurons showed more than a doubling of visually evoked firing rate as the animal transitioned from standing still to running..’ (Niell, Stryker, 2010)

Our current EEG in the wild tools:
Imaging with the smartphone brain scanner (SBS [YouTube link](#))
EarEEG non-invasive, discreet
Hyposafe's subcutaneous electrode device

Example SBS: engagement in the classroom
Example EarEEG: the scalp to ear link
Example UNEEG Medical’s Hyposafe device: 40+ days sampling in the wild

Limits of Predictability in Human Mobility

Chaoming Song, Zehui Qu, Nicholas Blumm, Albert-László Barabási

Fig. 1. (A) Trajectories of two anonymized mobile phone users who visited the vicinity of $N = 22$ and 76 different towers during the 3-month-long observational period. Each dot corresponds to a mobile phone tower, and each time a user makes a call, the closest tower that routes the call is recorded, pinpointing the user's approximate location. The gray lines represent the Voronoi lattice, approximating each tower's area of reception. The colored lines represent the recorded movement of the user between the towers. (B) Mobility networks associated with the two users shown in (A). The area of the nodes corresponds to the frequency of calls the user made in the vicinity of the respective tower, and the widths of line edges are proportional to the frequency of the observed direct movement between two towers. (C) A week-long call pattern that captures the time-dependent location of the user with $N = 22$. Each vertical line corresponds to a call, and its color matches the tower from where the call was placed. This sequence of locations serves as the basis of our mobility prediction. (D) The distribution of the time intervals between consecutive calls, $\tau$, across the whole user population, documenting the nature of the call pattern as coming in bursts (11). (E) The distribution of the fraction of unknown locations, $q$, representing the hourly intervals when the user did not make a call, and thus his or her location remains unknown to us.

Basic data collection with the “Context Logger” tool (Nokia N95).

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Sampling</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerometer</td>
<td>30/minute</td>
<td>3D Accelerometer values</td>
</tr>
<tr>
<td>GSM</td>
<td>1/minute</td>
<td>CellID of GSM base transceiver station</td>
</tr>
<tr>
<td>GPS</td>
<td>2–3/hour</td>
<td>Longitude, Latitude, and Altitude</td>
</tr>
<tr>
<td>Bluetooth</td>
<td>20–40/hour</td>
<td>Bluetooth MAC, friendly name, and device type</td>
</tr>
<tr>
<td>WLAN</td>
<td>1/minute</td>
<td>Access Point MAC address, SSID, and RX level</td>
</tr>
<tr>
<td>Phone activity</td>
<td>Event</td>
<td>Phone number and direction of call or message</td>
</tr>
</tbody>
</table>

Table 1. List of embedded mobile phone sensors used for collecting data

N= 14 participants took part in the experiment between 31 to 71 days, resulting in approximately 472 days of data covering data collection periods totalling 676 days. The average duration was 48.2 days.

Current experimental platform “Copenhagen Network Study” is based on 1000 students!
Fig. 5. Predictive Information (normalized) vs. window length (log scale). Participant 3 is left out.
24/7 Neurotechnology - Aim: Connect cognitive neuroscience and normal behaviors

Conventional EEG system

Wearable EEG system

Ear-EEG/Hyposafe device

High-performance research and clinical EEG system

Discreet, unobtrusive and user-friendly assistive devices for everyday life

Smartphone data

Brain state representations connected by machine learning
Smartphone brain scanner @ youtube
Mobility projects

Social EEG-
- Joint attention

Mobile real-time EEG Imaging
- Neurofeedback
- Digital media & emotion
- Bhutan Epilepsy Project

Simon Kamronn
Andreas Trier Poulsen

Camilla Falk
Smartphone Brain Scanner

Based on the Emotiv wireless transmission mechanism w/ the EPOC head set or modified EasyCaps (Stefan Debener, Oldenburg)

Version SBS2.0 for generic Android platforms (Tested in Galaxy Note, Nexus 7,...)

https://github.com/SmartphoneBrainScanner


SBS2 functions

Real time system
- Bayesian minimum norm 3D reconstruction with a variety of forward models (N=1024).
- Adaptive SNR model (β,α) estimated every 10 sec.
- Update speed ~ 40 fps (Emotiv sample rate 128Hz, blocks of 8 samples)
- Selected frequency band option
- Spatial averaging in “named” AAL regions

Mobile experiment set-ups, so far...
- Common spatial pattern- BCI
- Stimulus presentation options: video, image, text, audio
- Neuro-feedback
EEG imaging

Linear ill-posed inverse problem

\[
X: \ N \times T \\
Y: \ K \times T \\
A: \ K \times N \\
N >> K
\]

Need priors to solve!

SBS: smoothness
- minimum norm
Bayesian inference / 10 sec.

\[
Y_{k,t} = \sum_{n=1}^{N} A_{k,n} X_{n,t} + E_{k,t}.
\]

Do we get meaningful 3D reconstructions?

Imagined finger tapping
Left or right cued (at t=0)

Signal collected from an AAL region (n=80)


Imaging engagement in the classroom

JP. Dmochowski et al, "Correlated components of ongoing EEG point to emotionally laden attention a possible marker of engagement?" Frontiers of Human Neuroscience, 6:112, April 2012.


S Kamronn Poulsen AT, Hansen LK. Multiview Bayesian correlated component analysis. Neural computation. 2015.

Reproducing Parra’s intersubject correlation with classroom EEG

Figure 1. Experimental setup for joint viewings. (Left) 9 subjects where placed on a line to induce a cinema-like experiences. (Right) Subjects seen from the back, watching films projected onto a screen. Tablets recording EEG are resting on the tables behind the subjects. The signal is transmitted wirelessly from each subject.
intersubject correlation ..towards a mechanism

Figure 4. The ISC of the first CorrCA component is temporally correlated with the average luminance differences (ALD) of the film stimulus. ALD is calculated as the frame-to-frame difference in pixel intensity, smoothed to match the 5s window of ISC, and mainly reflects the frequency of changes in camera position. Data computed from the neural responses of subjects watching Bang You're Dead.

Figure 5. Relation between the ISC and the ALD for different conditions. Each point indicates a point in the ISC time course as seen in Fig. 2a (5 s windows, 80% overlap) and the corresponding ALD calculated from the visual stimulus. It is evident that time points with higher luminance fluctuations (high ALD) result in higher correlation of brain activity across subjects (high ISC). The indicated “slope” is a least squares fit of the slope of lines passing through (0, 0). The slope indicates the strength of ISC for a given ALD value. For both films there is a significant drop in the slope (p < 0.01; block permutation test with block size B = 25 sec), thus the original narrative (blue) elicits higher ISC than the less engaging scrambled version of the films (red). Note that brightness of the scenes in Sophie's Choice is much lower than in Bang! You're dead, resulting in an ALD that is lower by almost a factor 10.
Neurotech for 24/7 brain state monitoring: EarEEG

**Aim:**

A discrete, non-invasive solution for long time recording in the wild

**Status**

EarEEG is in well-working prototype

Classical EEG reproduced: Sustained and event related responses to audio and visual stimulus

**High mutual information between ear and scalp EEG**

Neurotech for 24/7 brain state monitoring: EarEEG

On the keyhole hypothesis: High mutual information between Ear and Scalp EEG

Kaare B. Mikkelsen^a, Preben Kidmose^b,* Lars Kai Hansen^b

![Image of brain diagrams and graphs]

Figure 4: Prediction correlation, ρ, as a function of time since training (in blue). Shown in red is prediction correlation for a model trained on data within the last 10 minutes. Gaps correspond to data missing in the original data set.

![Image of brain maps]

(a) Using only the left ear.

(b) Decoupled ears.

(c) Coupled ears, with common reference.
Debener & Vos’s mobile EEG devices

Maarten De Vos, Oxford + Neuropsychology at the University of Oldenburg, CRITIAS and Sonomax, Canada.

Stefan Debener, Maarten De Vos, Neuropsychology at the University of Oldenburg,

Towards a truly mobile auditory brain–computer interface: Exploring the P300 to take away
Maarten De Vos a,b,c, Katharina Gandras a, Stefan Debener a,b,c
Oticon mobile EEG device

United States
Patent Application Publication
LUNNER

Pub. No.: US 2016/0081623 A1
Pub. Date: Mar. 24, 2016

HEARING ASSISTANCE SYSTEM COMPRISING ELECTRODES FOR PICKING UP BRAIN WAVE SIGNALS
U.S. Cl.
CPC: A61B 5/00 (2013.01); G06F 3/0133 (2013.01); H04R 25/05 (2013.01); H04R 25/53 (2013.01); A61B 5/0074 (2013.01); A61B 5/0066 (2013.01); A61B 5/0024 (2013.01); H04R 222/06 (2013.01); 2566/0068 (2013.01)

Applicant: Oticon A/S, Smeerum (DK)
Inventor: Thomas LUNNER, Smeerum (DK)
Assignee: Oticon A/S, Smeerum (DK)

ABSTRACT
**Aim:**

Permanent recording in the wild - Decoding hypoglaemia risk

**Status**

Very stable subcutaneous electrode

Magnetic coupling (signal / power) with outside ear piece

Signal is highly correlated with surface electrode in same location

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How does (partial) mind wandering vary during the day?

How does a brain on vacation differ from a working brain?

Methods:
Power spectrum over 3 sec win / 2 sec overlap as basic features
Clustering. Manually identify (2) alpha clusters;
Assign power spectra over 45 days to clusters...

Analytic strategy

Challenge: Ultra-long sequences, seasonal, non-stationary data, with significant artefactual episodes and "missing data"
Short term predictability
Fano Ineq. Bound on predictability of spectral microstates (ts=1 sec)

Predictability
High at night,
lowest during "leisure time"
Privacy... it’s human to share

Intuitive data
Images, speech, economical, commercial, location, individual thoughts

Non-intuitive data
Health: diet, complete motion patterns
Physiology: heart beat, skin resistance, gaze, brain data, your mind set

Sandy Pentland calls for “a new deal on data” with three basic tenets:

1) you have the right to possess your data,
2) to control how it is used,
3) to destroy or distribute it as you see fit.

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Privacy for Personal Neuroinformatics
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