EEG brain state monitoring in the wild

Lars Kai Hansen
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Conventional EEG system

High-performance research and clinical EEG system

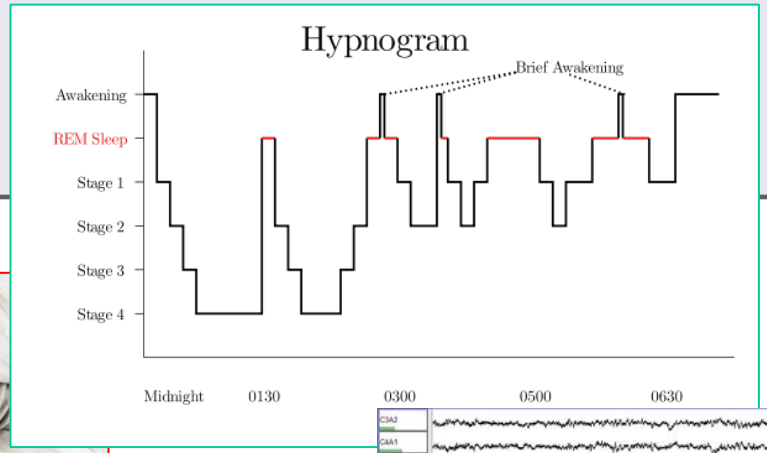
Wearable EEG system

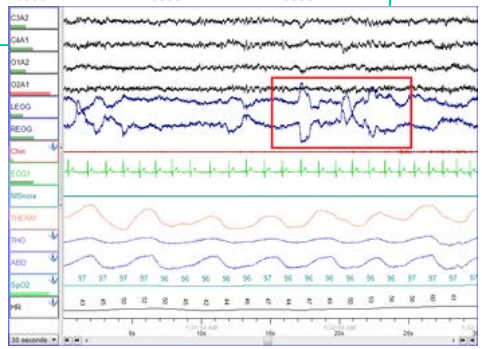
Discreet, unobtrusive and user-friendly assistive devices for everyday life

Ear-EEG/Hyposafe device

Smartphone data

How did you sleep last night?



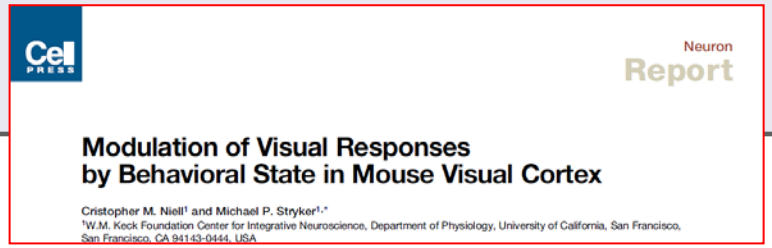


..we have only limited quantitative self insight...

hard to explain your “state” to services, psychiatrists, caretakers etc

My working hypothesis: <u>In the wild brain scanning</u> has the potential to help us infer brain states, plans and wishes, and in this way improve services, diagnosis, medication, and rehabilitation

OUTLINE


Cell PRESS

Neuron
Report

Modulation of Visual Responses by Behavioral State in Mouse Visual Cortex

Cristopher M. Niell[1] and Michael P. Stryker[1,*]
[1]W.M. Keck Foundation Center for Integrative Neuroscience, Department of Physiology, University of California, San Francisco, San Francisco, CA 94143-0444, USA

Why sampling in the wild?

A science of the individual - new research questions..

‘cognition is action’ (Engell et al, 2013)

‘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, discreete

Hyposafe's subcutaneous eletrode device

Example SBS: engagement in the classroom

Example EarEEG: the scalp to ear link

Example Hyposafe device: 40+ days sampling in the wild

Engel, Andreas K., et al. "Where's the action? The pragmatic turn in cognitive science." *Trends in cognitive sciences* 17.5 (2013): 202-209.
Niell, Cristopher M., and Michael P. Stryker. "Modulation of visual responses by behavioral state in mouse visual cortex." *Neuron* 65.4 (2010): 472-479.

Why brain state decoding? Services …

*"**Oticon Tego** is directed by the DecisionMaker system, driven by (AI) Artificial Intelligence that processes sound intelligently. This super advanced form of computer processing. Artificial Intelligence is the process of performing logical operations enthused by the human brain.*

The difference between AI-based and conventional instruments is distinct: AI-based instruments constantly adapt to particular situation where conventional instruments provide only a fixed response to selected types of sounds. AI-based, Oticon Tego evaluates the different sound processing options and selects the one guaranteed to give the clearest sound quality.

What if this was based on brain state?? e.g., attention

Just like the brain, OticonTego filters out the noise so you can concentrate on the speech you like to hear. The DecisionMaker system evaluates and decides exactly when and how to apply the various features to get the best speech understanding and sound quality in any situation. <u>All the processing happens automatically, so you need not lift a finger at all!</u> Completely hands-free Oticon Tego is an ideal hearing solution for the active you!"

http://www.hearingaids123.com/oticon-tego

Why brain state decoding? To make up for cognitive biases

Human senses & brains are not optimal from a behavioral point of view...

..e.g. the list of cognitive biases in Wikipedia

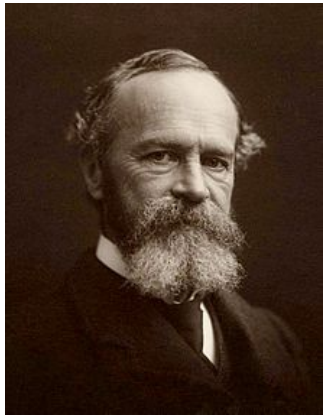
Ambiguity effect	The tendency to avoid options for which missing information makes the probability seem "unknown."[8]
Anchoring or focalism	The tendency to rely too heavily, or "anchor," on one trait or piece of information when making decisions (usually the first piece of information that we acquire on that subject)[9][10]
Attentional bias	The tendency of our perception to be affected by our recurring thoughts.[11]
Availability heuristic	The tendency to overestimate the likelihood of events with greater "availability" in memory, which can be influenced by how recent the memories are or how unusual or emotionally charged they may be.[12]
Availability cascade	A self-reinforcing process in which a collective belief gains more and more plausibility through its increasing repetition in public discourse (or "repeat something long enough and it will become true").[13]
Backfire effect	When people react to disconfirming evidence by strengthening their beliefs.[14]
Bandwagon effect	The tendency to do (or believe) things because many other people do (or believe) the same. Related to groupthink and herd behavior.[15]
Base rate fallacy or base rate neglect	The tendency to ignore base rate information (generic, general information) and focus on specific information (information only pertaining to a certain case).[16]
Belief bias	An effect where someone's evaluation of the logical strength of an argument is biased by the believability of the conclusion.[17]
Bias blind spot	The tendency to see oneself as less biased than other people, or to be able to identify more cognitive biases in others than in oneself.[18]
Cheerleader effect	The tendency for people to appear more attractive in a group than in isolation.[19]

http://en.wikipedia.org/wiki/List_of_cognitive_biases

What can be decoded - Stereotypical behaviors?

"When we look at living creatures from an outward point of view, one of the first things that strike us is that they are bundles of habits."

"In wild animals, the usual round of daily behavior seems a necessity implanted at birth; in animals domesticated, and especially in man, it seems, to a great extent, to be the result of education. The habits to which there is an innate tendency are called instincts; some of those due to education would by most persons be called acts of reason."



"It thus appears that habit covers a very large part of life, and that one engaged in studying the objective manifestations of mind is bound at the very outset to define clearly just what its limits are."

William James, The Principles of Psychology (1890)
CHAPTER IV "Habit"

Limits of Predictability in Human Mobility

19 FEBRUARY 2010 VOL 327 SCIENCE

Chaoming Song,[1,2] Zehui Qu,[1,2,3] Nicholas Blumm,[1,2] Albert-László Barabási[1,2]*

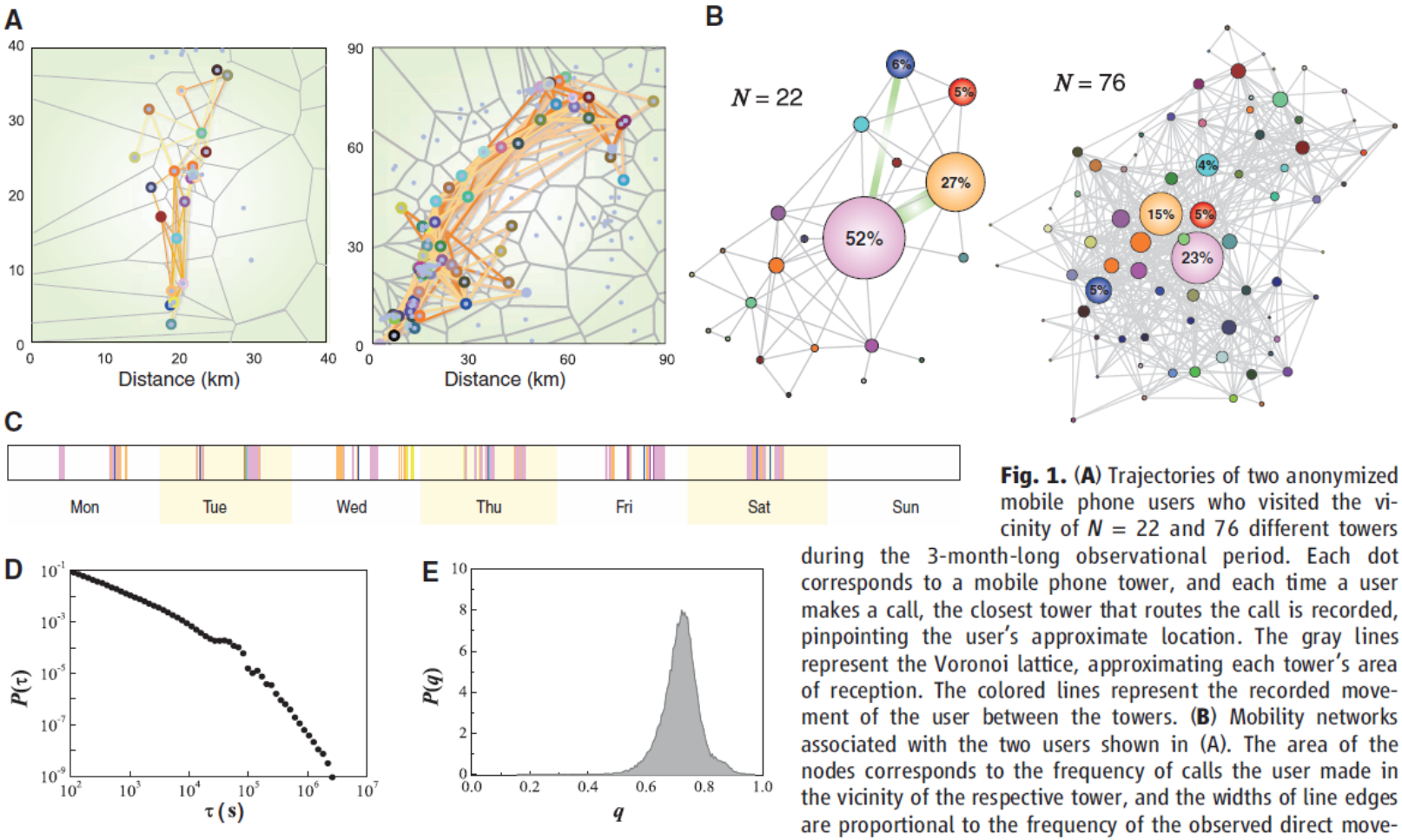


Fig. 1. (**A**) Trajectories of two anonymized mobile phone users who visited the vicinity of N = 22 and 76 different towers during the 3-month-long observational period. Each dot corresponds to a mobile phone tower, and each time a user makes a call, the closest tower that routes the call is recorded, 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, τ, 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.

Short time predictability @ DTU (N=14)

B.S. Jensen, J.E. Larsen, K. Jensen, J. Larsen, L.K. Hansen: Estimating Human Predictability From Mobile Sensor Data
In Proc. IEEE International Workshop on Machine Learning for Signal Processing MLSP (2010).
B.S. Jensen, J.E. Larsen, K. Jensen, J. Larsen, L.K. Hansen: Predictability of mobile phone associations.
In Proc. 21st European Conference on Machine Learning, Mining Ubiquitous and Social Environments Workshop. Barcelona, Spain (2010).

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

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

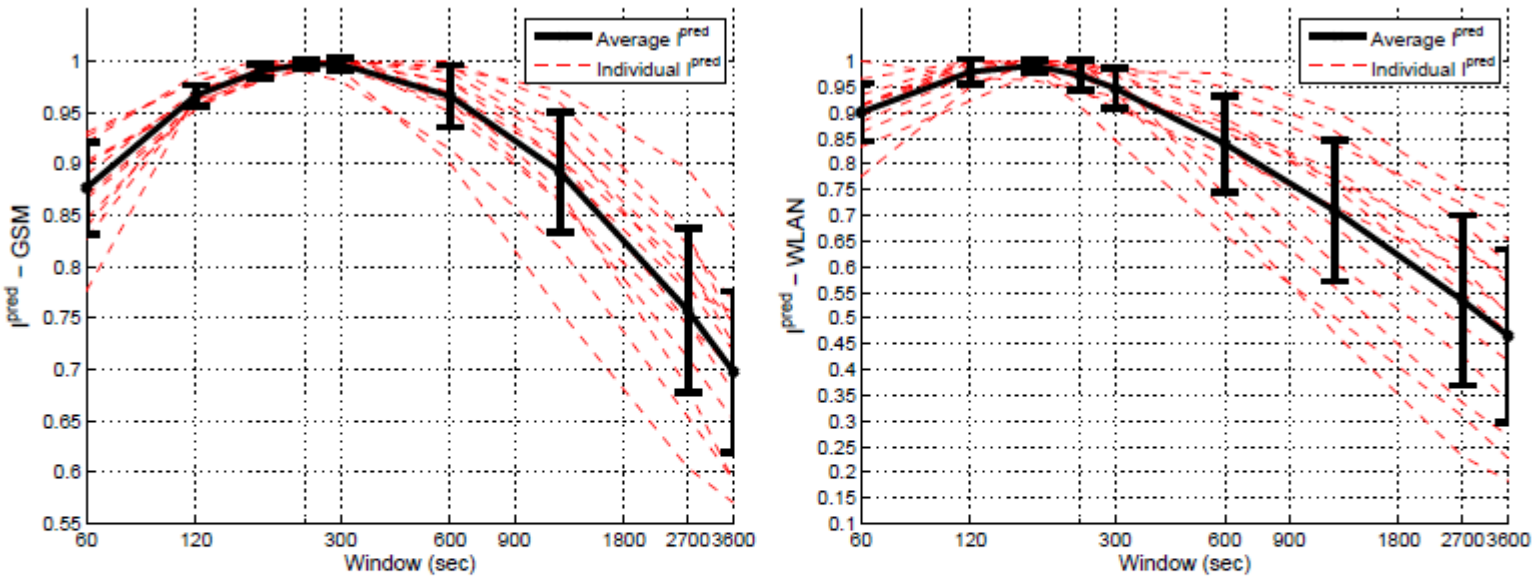
Table 1. List of embedded mobile phone sensors used for collecting data

The experiment started October 28, 2008 and ended January 7, 2009.

Participants were students and staff members from The Technical University of Denmark volunteering to be part of the experiment. Thus mainly situated in the greater Copenhagen area, Denmark.

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.

Predictability vs time scale



(a) GSM (b) WLAN

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

High-performance research and clinical EEG system

Wearable EEG system

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

Ear-EEG/Hyposafe device

Smartphone data

Brain state representations connected by machine learning

DTU mobility projects

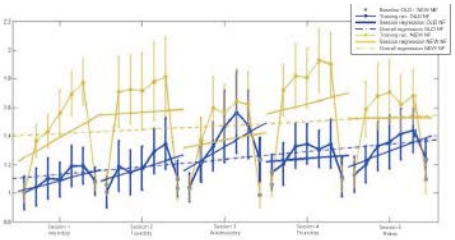
Social EEG-
- -Leaders and followers
- -Joint attention

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

Ivana Konvalinka

Simon Kamronn

Andreas Trier Poulsen



Camilla Falk

Farrah J. Mateen, Massachusetts General Hospital

Machine learning to decode personal states

Aims to extract the mutual information between personal state and quantifiable behavior

- **Personal state**: Macroscopic variables, tags, behavioral categories … *s(t)*

- **Sensed behaviors**: Micro/meso-scopic data/variables … *x(t)*

- **Mutual information** is captured in the joint distribution … *p(x,s).*

Supervised machine learning methods assume s(t) or parts of s(t) known … unsupervised methods consider s(t) "hidden"…..

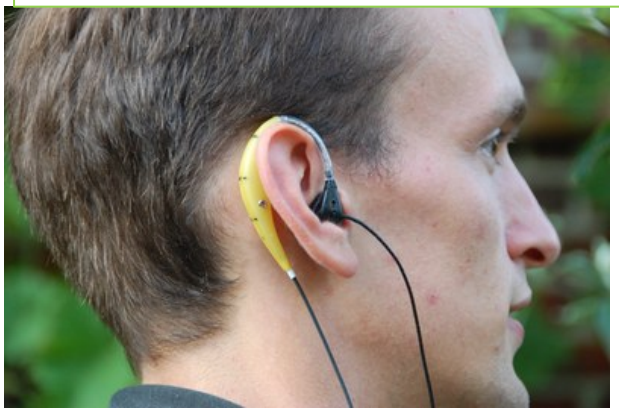
and builds predictive models of the relation

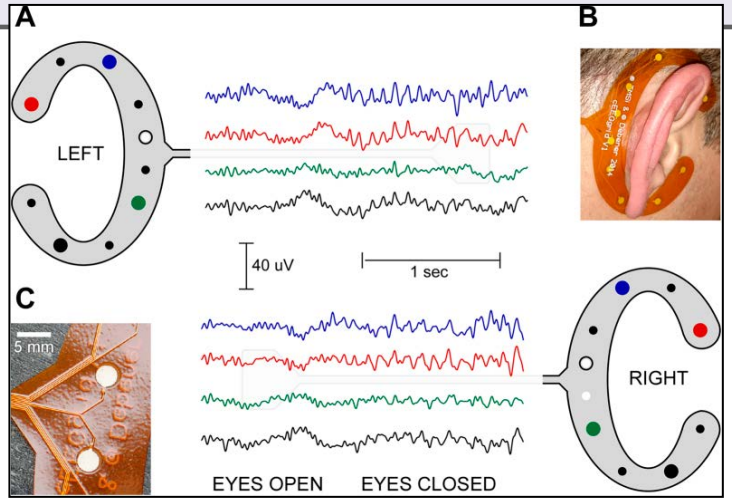
24/7 Neurotech – the devices

EmoCap

Stefan Debener's mobile EEG devices

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



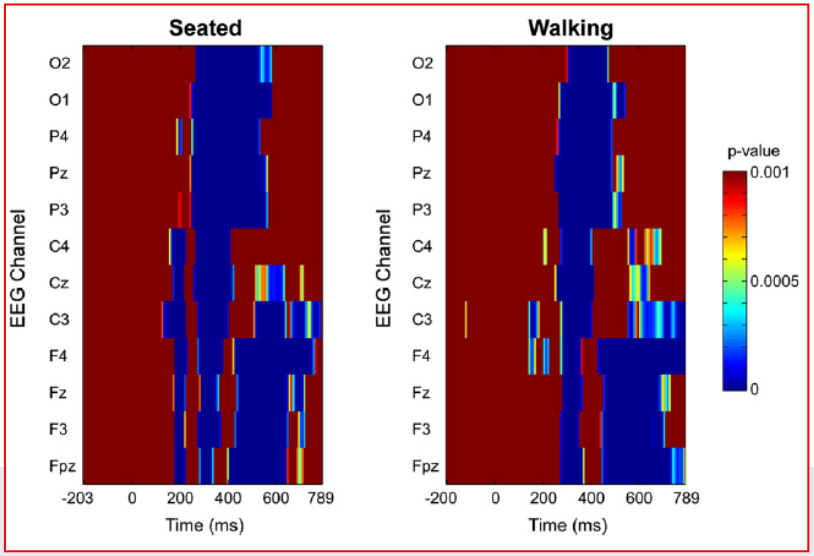


Stefan Debener, Maarten De Vos,
Neuropsychology at the University of Oldenburg,

Towards a truly mobile auditory brain–computer interface: Exploring the P300 to take away

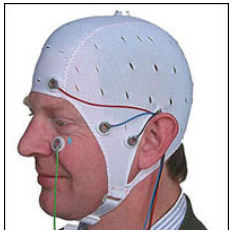
Maarten De Vos [a,b,c,*], Katharina Gandras [a], Stefan Debener [a,b,c]

Fig. 1. The mobile EEG system as proposed by Debener et al. (2012) consists of an amplifier-power supply unit, which is attached to the cap at the back of the head (weight 48 g, size 49 × 49 × 21 mm).



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

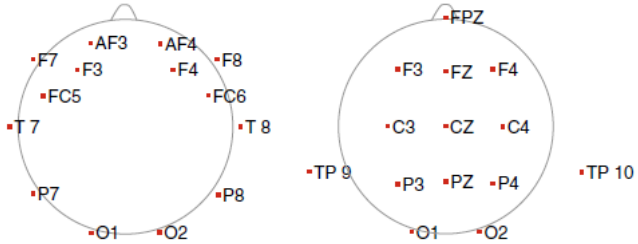
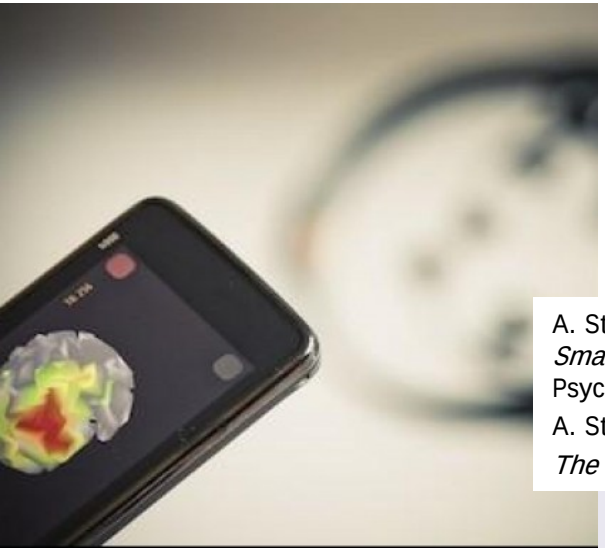


Fig. 5. Electrode locations for two mobile 16 channel EEG setups; the Emotiv neuroheadset using saline sensors positioned laterally (left), versus a standard gel-based Easycap EEG montage including central and midline positions (right).



A. Stopczynski, C. Stahlhut, M.K. Petersen, J.E. Larsen, C.F. Jensen, M.G. Ivanova, T.S. Andersen, L.K. Hansen. *Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeed-back.* International Journal of Psychophysiology, (2014).

A. Stopczynski, C. Stahlhut, J.E. Larsen, M.K. Petersen, L.K. Hansen. *The Smartphone Brain Scanner: A Portable Real-Time Neuroimaging System.* PloS one 9 (2), e86733, (2014)

SBS2 functions current

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

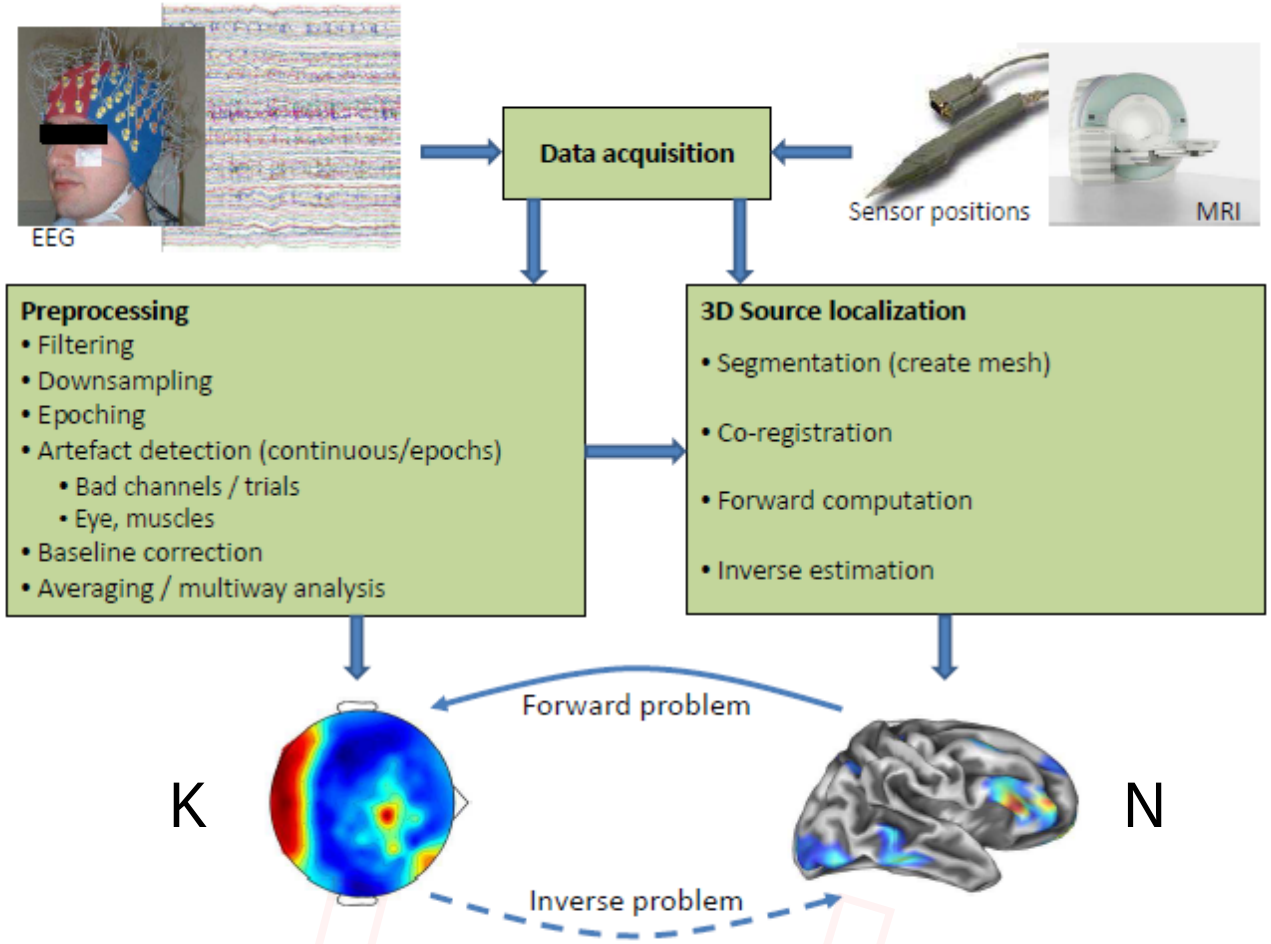
EEG imaging

Linear ill-posed inverse problem

X: N x T
Y: K x T
A: K x N

N >> K

Need priors to solve!



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

C. Stahlhut: Functional Brain Imaging by EEG: A Window to the Human Mind. PhD-Thesis (2011), DTU Informatics

Why 3D real-time imaging?

Enable on-line visual quality control

Neurofeed applications can be based on activity in specific brain structures /networks

Context priors may relate to 3D location (from meta analysis)

Evidence that BCI /decoding can be improved by 3D representation

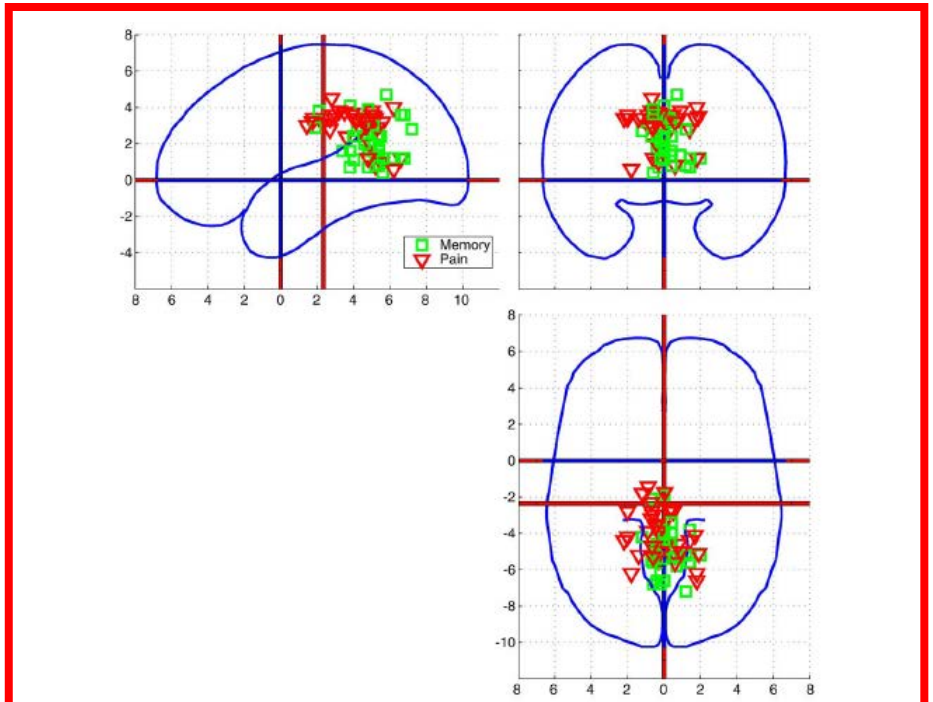


Fig. 3. Distribution of memory and pain brain activations in the posterior cingulate cortex shown on a sagittal plot: y is the AP axis with posterior as negative. The blue outline follows that of the Talairach atlas. The gray outline is an isocurvature in a probability volume for posterior cingulate cortex based on modeling of coordinates from the Brede database. Green squares are associated with "memory" articles and red triangles with "pain" articles.

Finn Årup Nielsen, Daniela Balslev, Lars Kai Hansen, "Mining the Posterior Cingulate: Segregation between memory and pain components". NeuroImage, 27(3):520-532, (2005)

Trujillo-Barreto, Nelson J., Eduardo Aubert-Vázquez, and Pedro A. Valdés-Sosa. "Bayesian model averaging in EEG/MEG imaging." NeuroImage 21, no. 4 (2004): 1300-1319.

Source representation can improve decoding

Besserve et al. (2011)

... reconstructing the underlying cortical network dynamics significantly outperforms a usual electrode level approach in terms of information transfer and also reduces redundancy between coherence and power features, supporting a decrease of volume conduction effects. Additionally, the classifier coefficients reflect the most informative features of network activity, showing an important contribution of localized motor and sensory brain areas, and of coherence between areas up to 6 cm distance.

Ahn et al. (2012)

... source imaging may enable noise filtering, and in so doing, make some invisible discriminative information in the sensor space visible in the source space.

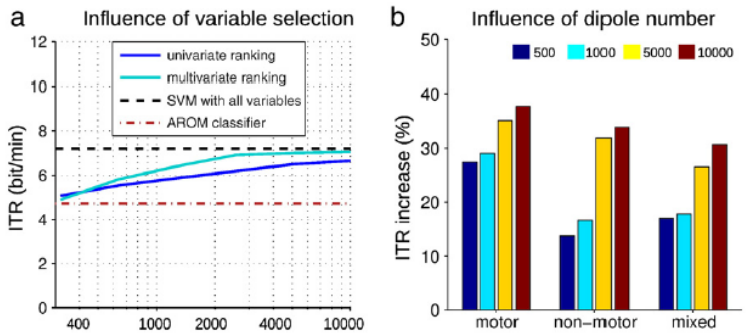


Fig. 6. Effect of reducing the number of sources or variables, for *power+coherence* quantification at the source level. a) Average ITR as a function of the number of variables for two variable ranking techniques: univariate ranking with a Student's *t*-test and multivariate ranking with the coefficient of a SVM classifier. The ITR values using a sparse number of variables with the AROM classifier (see text) and all variables with an SVM are plotted for comparison. b) Influence of the number of cortical dipoles used in the forward model on the ITR: percentage improvement of ITR with respect to electrode level quantification, for each type of couples of tasks (motor, non-motor and mixed couples).

Congedo, Marco, Fabien Lotte, and Anatole Lécuyer. "Classification of movement intention by spatially filtered electromagnetic inverse solutions." *Physics in Medicine and Biology* 51, no. 8 (2006): 1971

M Besserve, J Martinerie, L Garnero "Improving quantification of functional networks with eeg inverse problem:

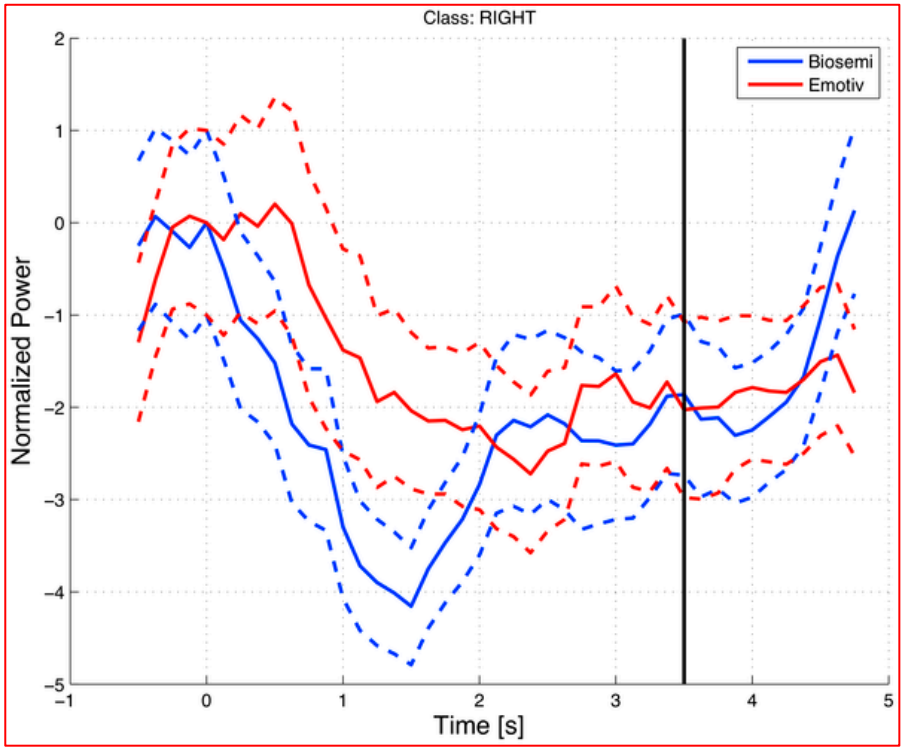
Evidence from a decoding point of view." *NeuroImage* 55.4 (2011): 1536-1547.

Minkyu Ahn, Jun Hee Hong, Sung Chan Jun: "Feasibility of approaches combining sensor and source features in brain–computer

interface." *Journal of Neuroscience Methods* 204 (2012): 168-178.

Edelman, Bradley J., Bryan Baxter, and Bin He. "EEG Source Imaging Enhances the Decoding of Complex Right-Hand Motor Imagery Tasks." *Biomedical Engineering, IEEE Transactions on* 63.1 (2016): 4-14.

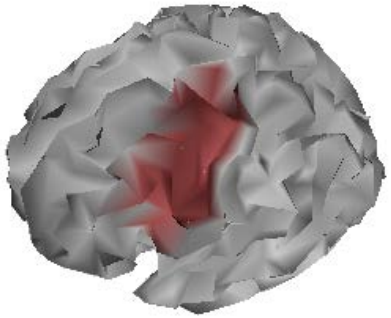
Do we get meaningful 3D reconstructions?

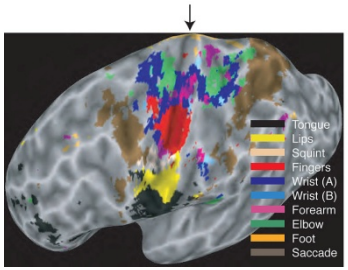


Imagined finger tapping

Left or <u>right</u> cued (at t=0)

Signal collected from an AAL region (n=80)





Meier, Jeffrey D., Tyson N. Aflalo, Sabine Kastner, and Michael SA Graziano. Complex organization of human primary motor cortex: a high-resolution fMRI study.Journal of neurophysiology 100(4) :800-1812 (2008).

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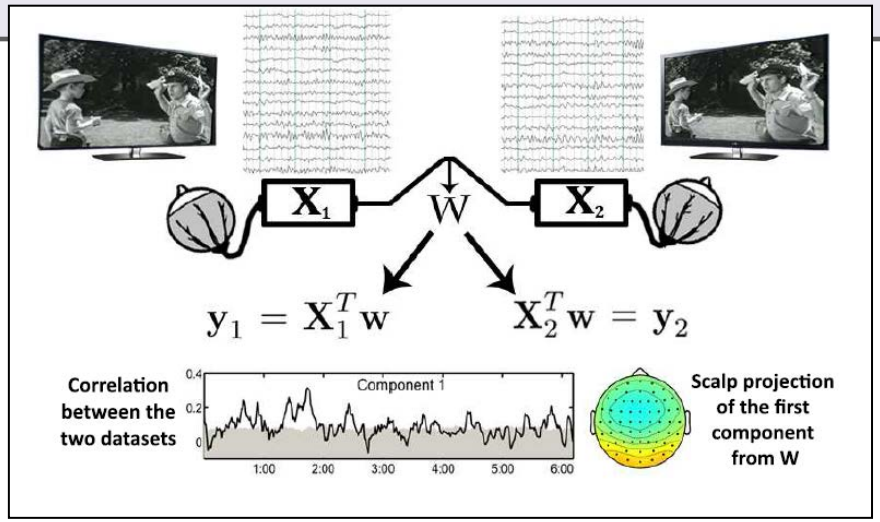
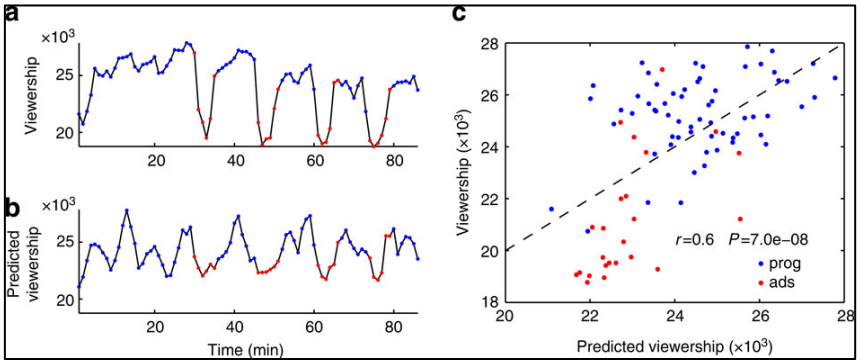
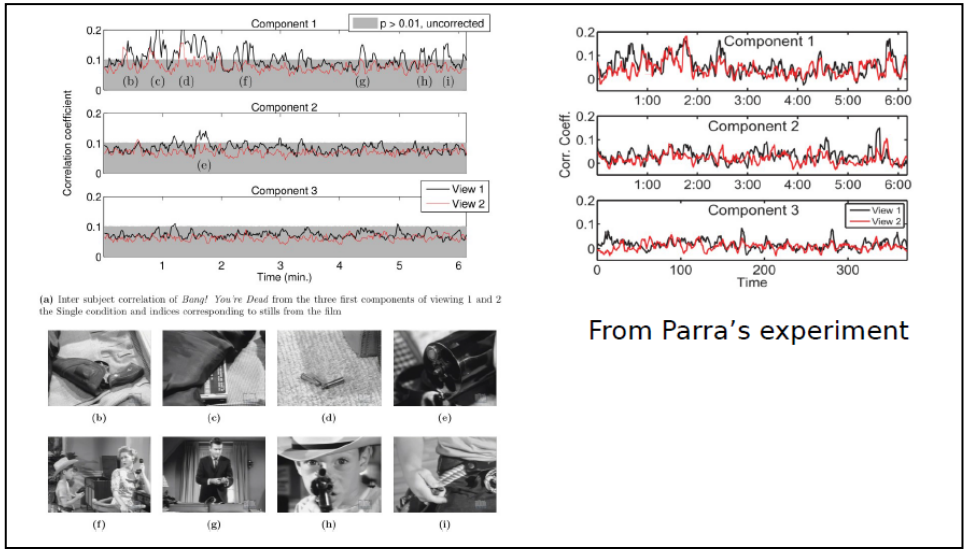
Imaging engagement in the classroom







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.

JP. Dmochowski et al, "Audience preferences are predicted by temporal reliability of neural processing", Nature Communications 5: 4567, July 2014.

AP Poulsen et al. "Measuring engagement in a classroom: Synchronised neural recordings during a video presentation." arXiv preprint arXiv:1604.03019 (2016).

Neurotech for 24/7 brain state monitoring: EarEEG

Aim:

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

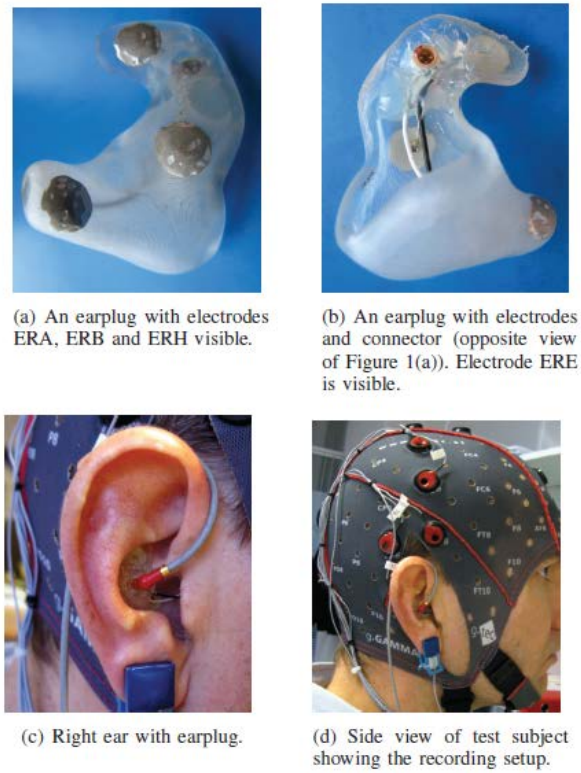
Status

EarEEG is a well-established technology

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

To appear:

High mutual information between ear and scalp EEG



(a) An earplug with electrodes ERA, ERB and ERH visible.

(b) An earplug with electrodes and connector (opposite view of Figure 1(a)). Electrode ERE is visible.

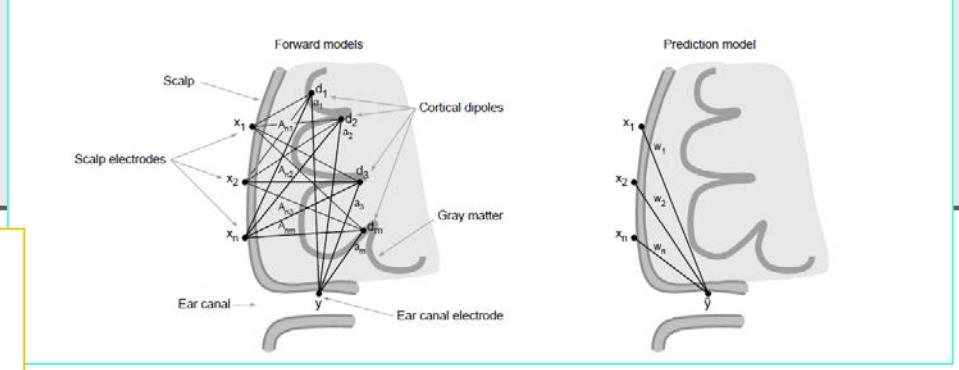
(c) Right ear with earplug.

(d) Side view of test subject showing the recording setup.

Fig. 1. View of a right ear earplug and the Ear-EEG recording setup.

Kidmose, Preben, et al. "Ear-EEG from generic earpieces: A feasibility study." *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*. IEEE, 2013.

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[a,*], Lars Kai Hansen[b]

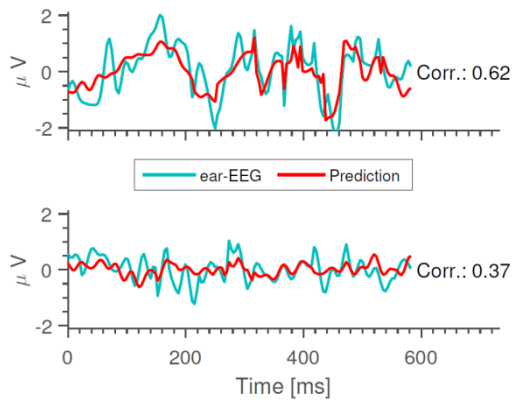


Figure 2: Short snippets of ear-EEG measurements together with their predictions.

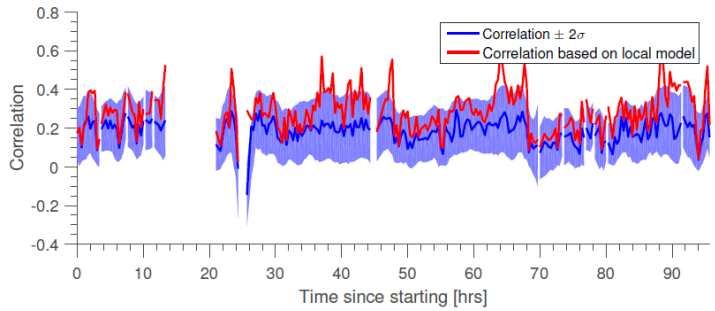
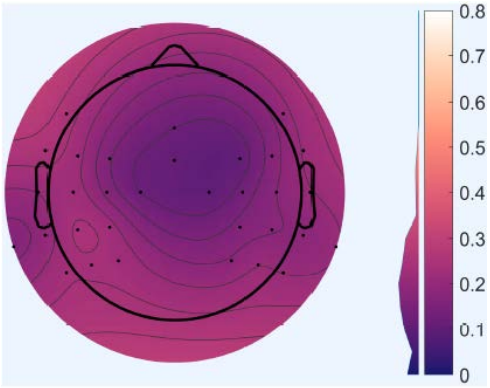
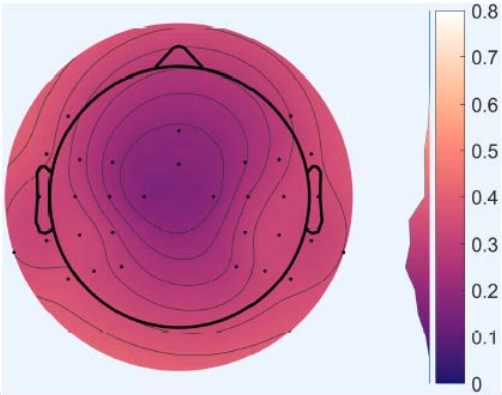


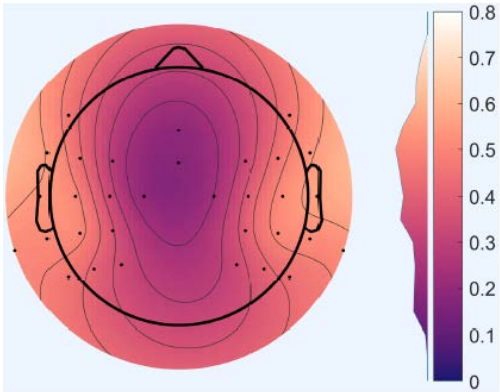
Figure 4: Prediction correlation, ρ, as a function of time since training (in blue). Shown in red is prediction correlation for a model trained on data within the last 10 minutes. Gaps correspond to data missing in the original data set.



(a) Using only the left ear.



(b) Decoupled ears.



(c) Coupled ears, with common reference.

Neurotech for 24/7 brain state monitoring: Hyposafe

Aim:

Permanent recording in the wild -

Decoding hypoglaemia risk

<u>Status</u>

Very stable subcutaneous electrode

Magnetic coupling (signal / power) with outside ear piece

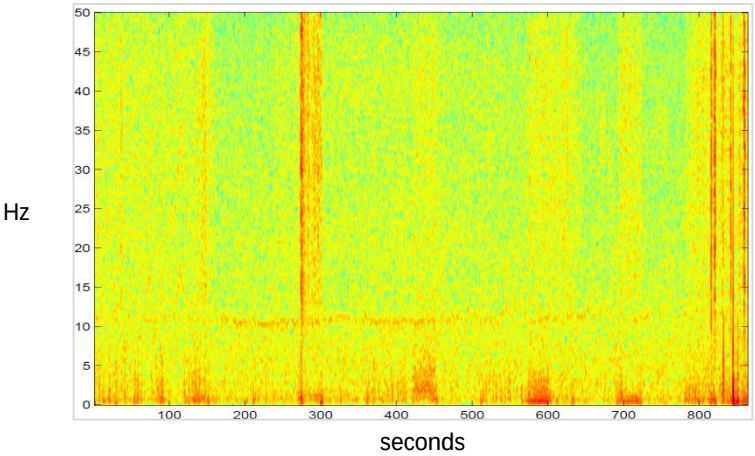
Signal is highly correlated with surface electrode in same location

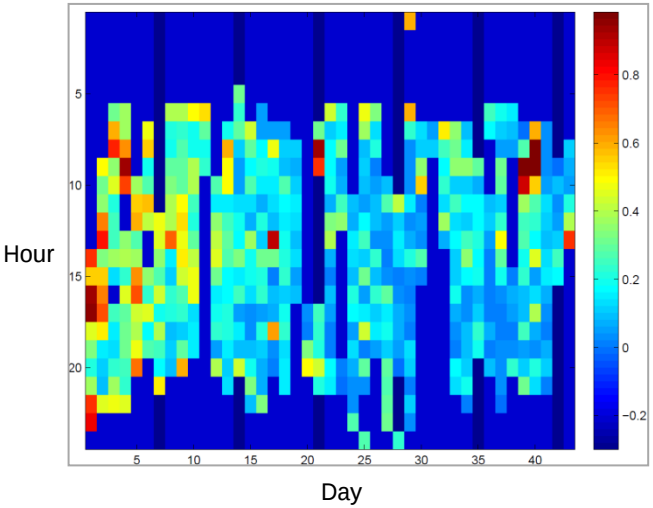
Illustration of
HypoSafe implantable device

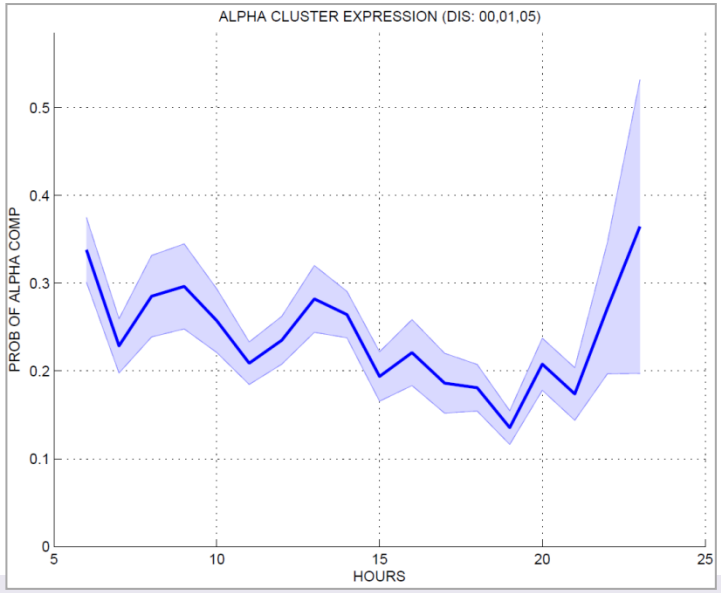
hypo safe®

Duun-Henriksen, Jonas, et al.
"EEG Signal Quality of a Subcutaneous Recording System Compared to Standard Surface Electrodes."
Journal of Sensors 2015 (2015).

Ultra long term brain decoding in healthy control: Hyposafe device







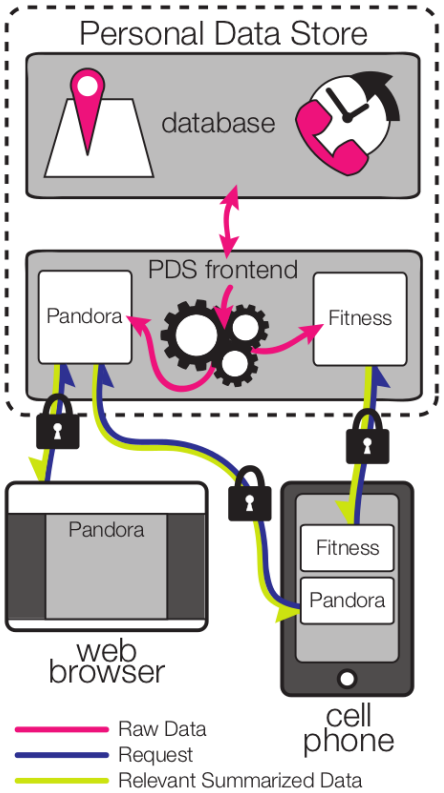
How does (partial) mind wandering vary during the day?

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

Methods:
Power spectrum over 3 sec windows as basic features
Fit 15 clusters. Manually identify (2) alpha clusters;
Assign 3 sec power spectra over 45 days to clusters...

Killingsworth, Matthew A., and Daniel T. Gilbert.
"A wandering mind is an unhappy mind." *Science* 330.6006 (2010): 932-932.

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.

Privacy for Personal Neuroinformatics

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2 MIT Media Lab
arks@dtu.dk, dazza@civics.com, lkai@dtu.dk, sandy@media.mit.edu

Conclusion

Human behavior is increasingly **quantified, modeled and predicted**

The key technology is **machine learning**

Decoding the brain is imminent: Simple brain states can be decoded with high accuracy…

… More complex mechanisms may be revealed with non-linear decoders even in high dimensional settings … and some care!

Not so distant future: Permanent 24/7 brain state decoding

Acknowledgment & Qs

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