Brain-computer interfaces

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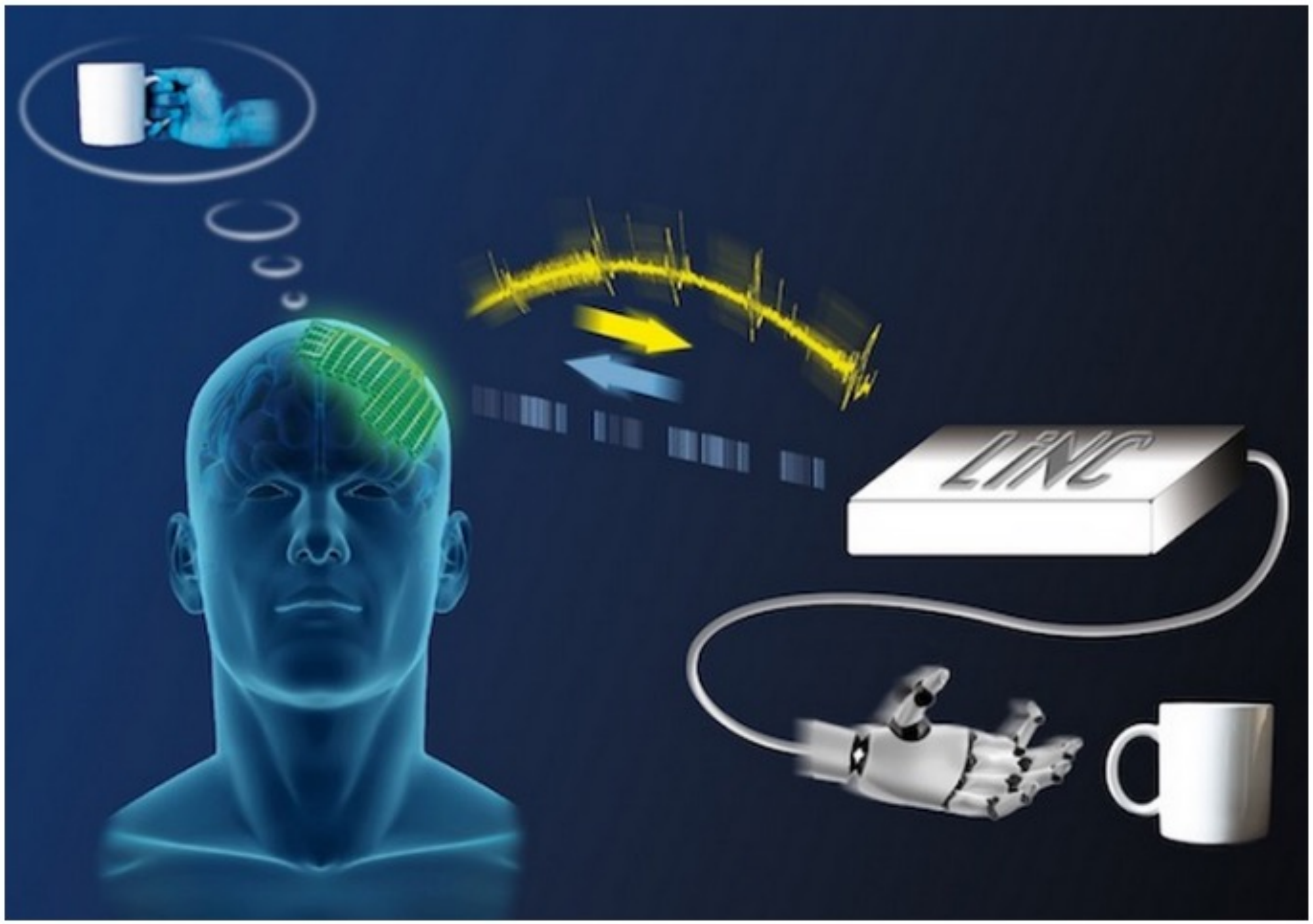
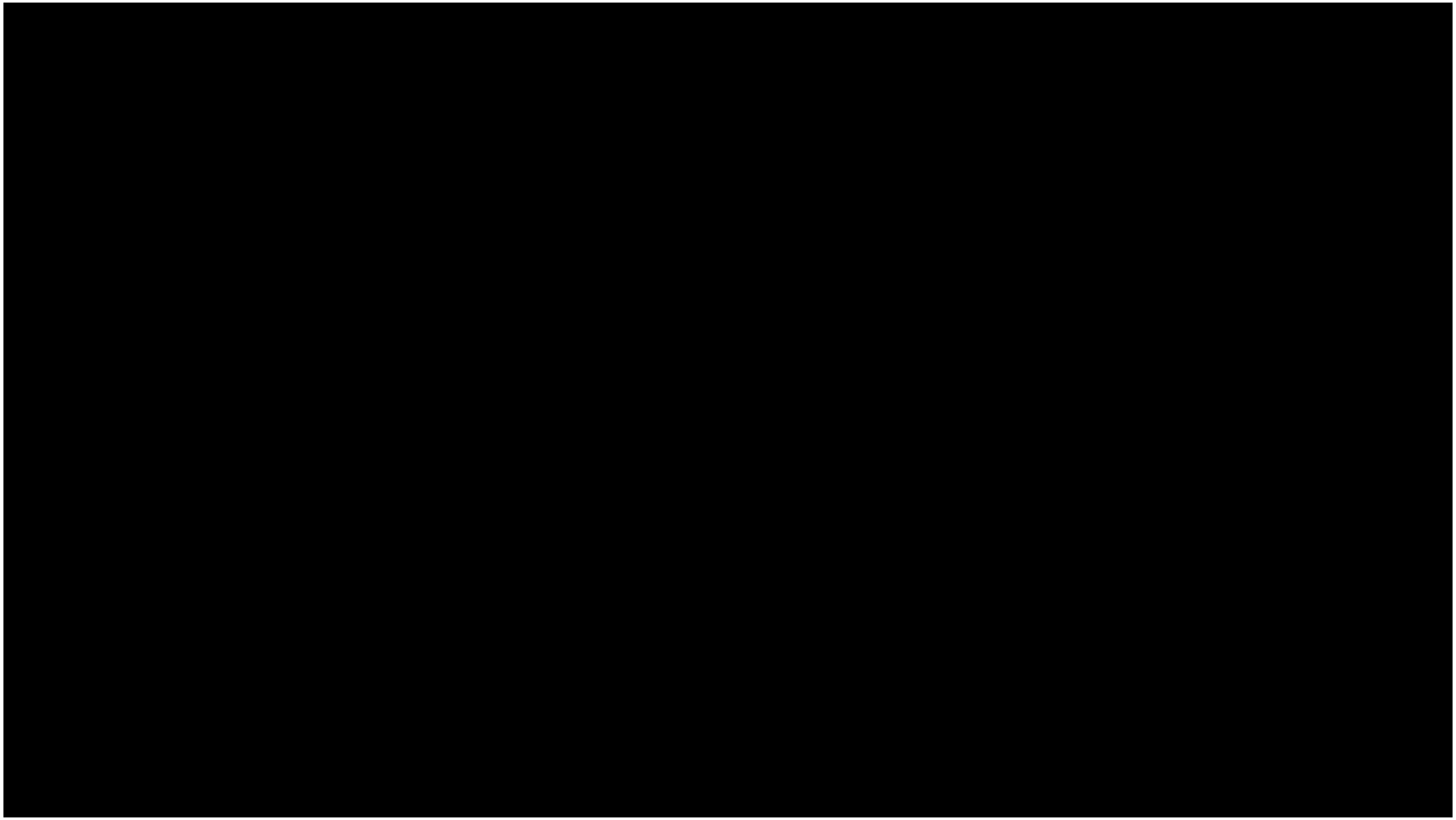
Outline ...

- What is a brain-machine interface (BMI) ?
- Examples of BMI
  - P300 (EEG)
  - SSVEP (EEG)
  - SCP (EEG)
  - MRP (EEG)
  - Biomimetic BMI (SUA)
- My own research
  - Biomimetic BMI (intracranial EEG)
  - Deep learning for BMI

What is brain-computer interface (BCI)?



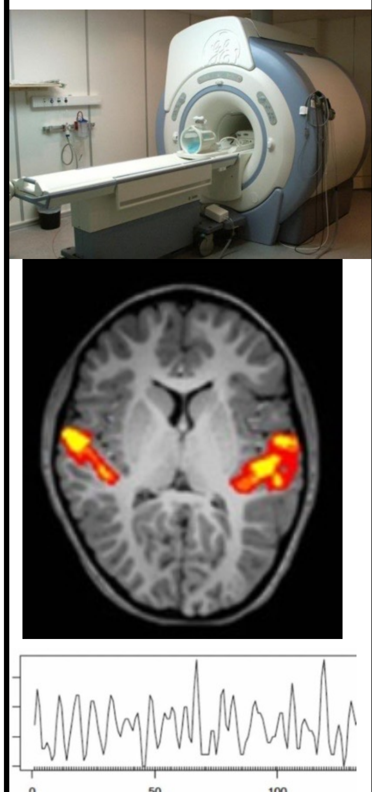
Brain-Computer Interface
Mysteries of the Brain



from YouTube

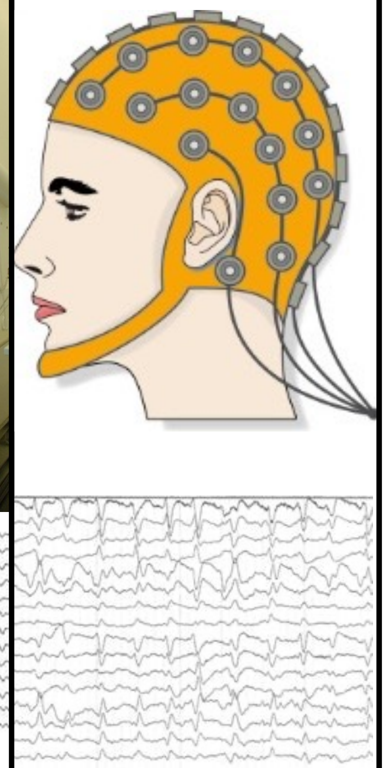
Overview of most common brain signals

fMRI
(funkční magnetická rezonance)

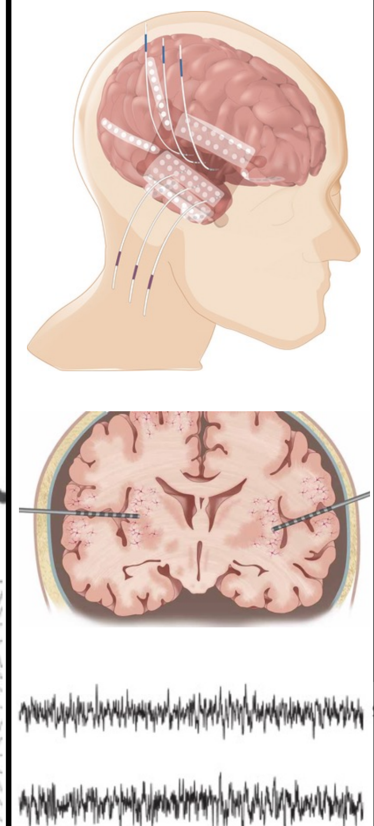


MEG
(magnetoencefalografie)

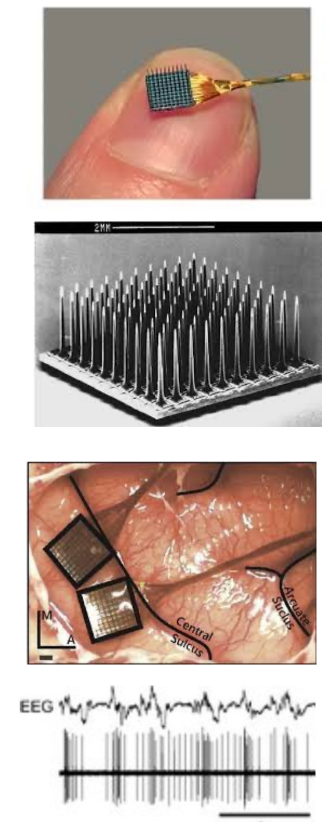
EEG
(elektroencefalografie)



intrakraniální EEG

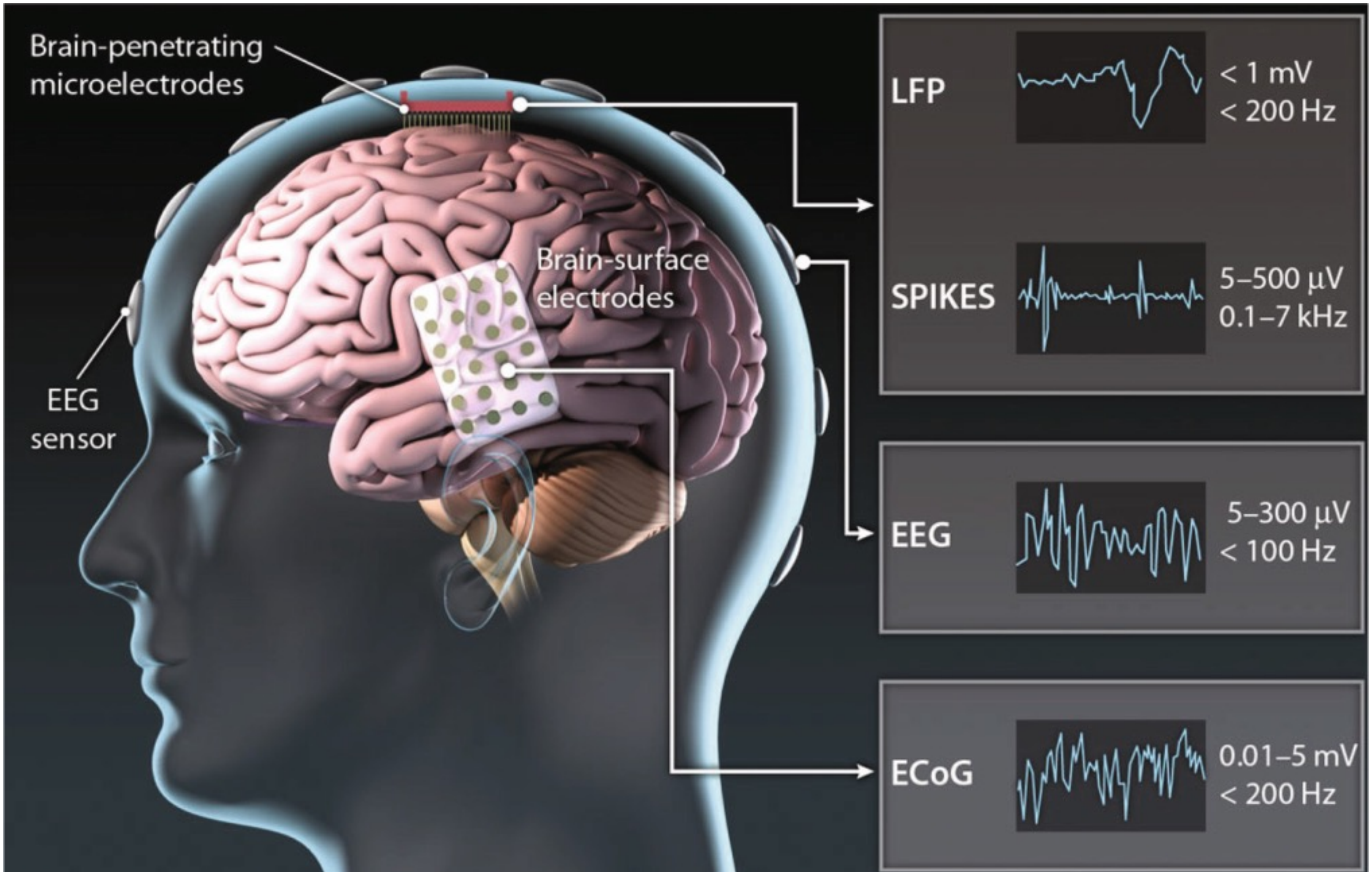


Aktivita neuronů



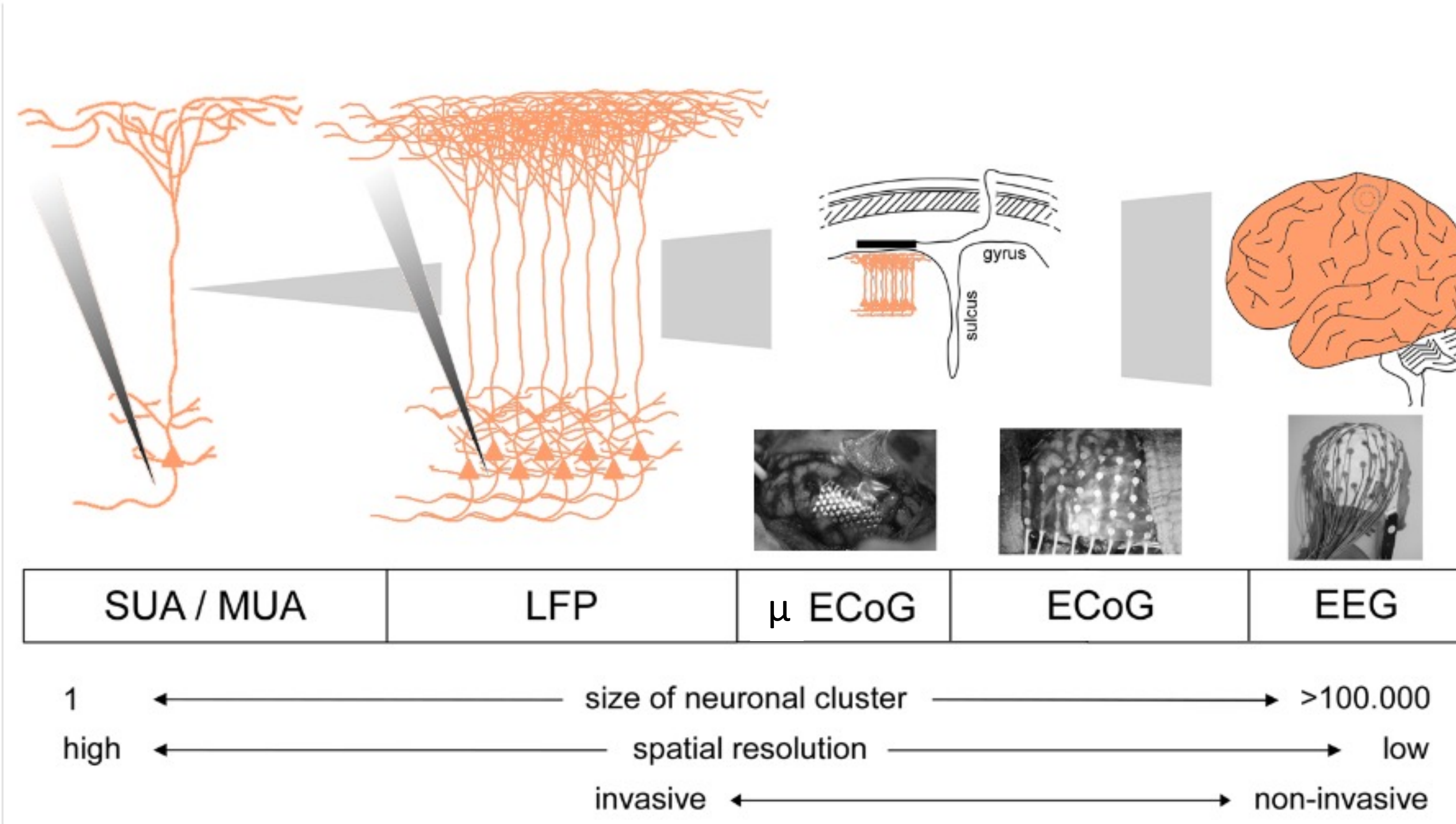
Zdroj obrázků: google (pictures)

Electrophysiological brain signals

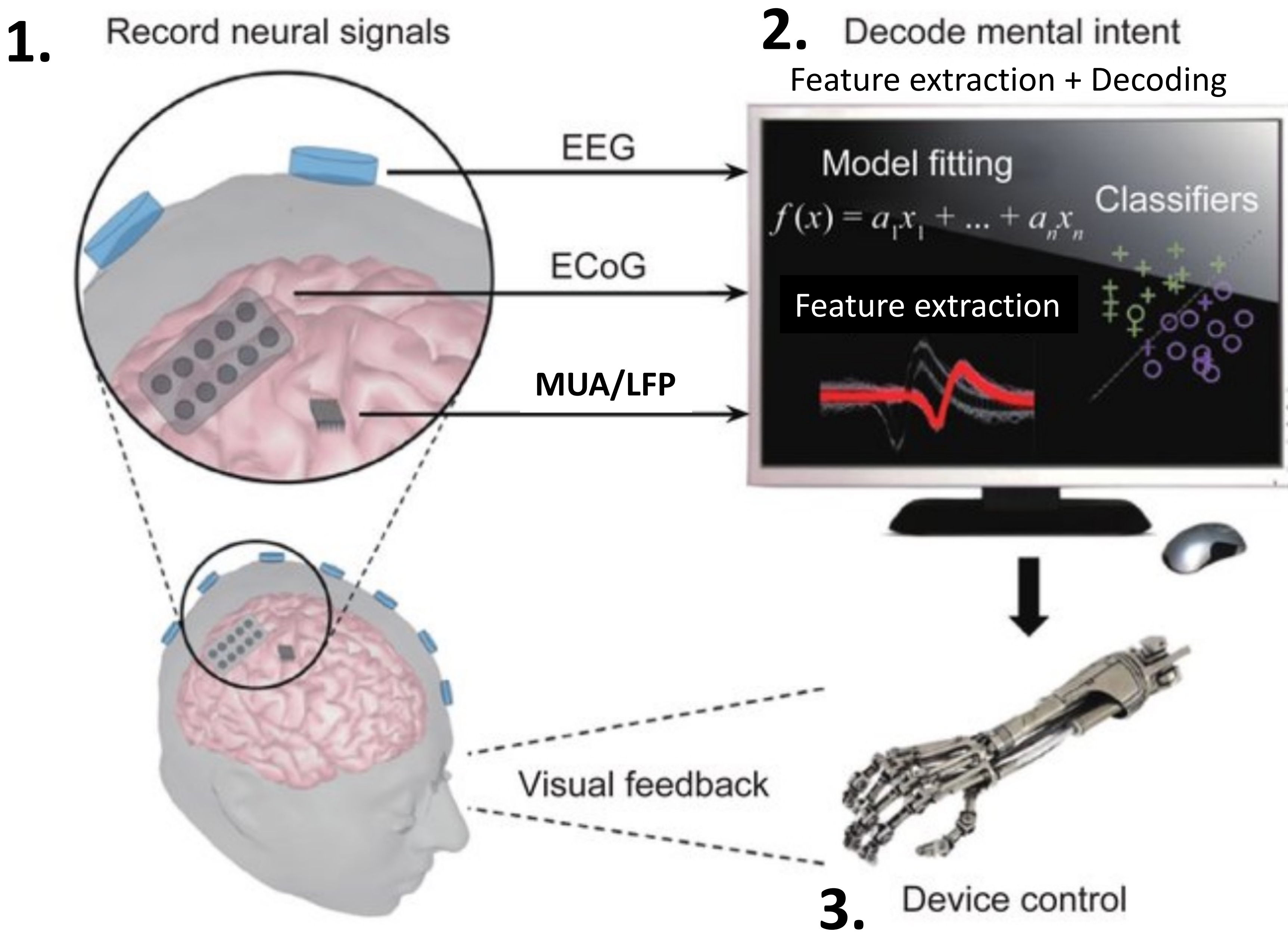


Türe et al. (2020)

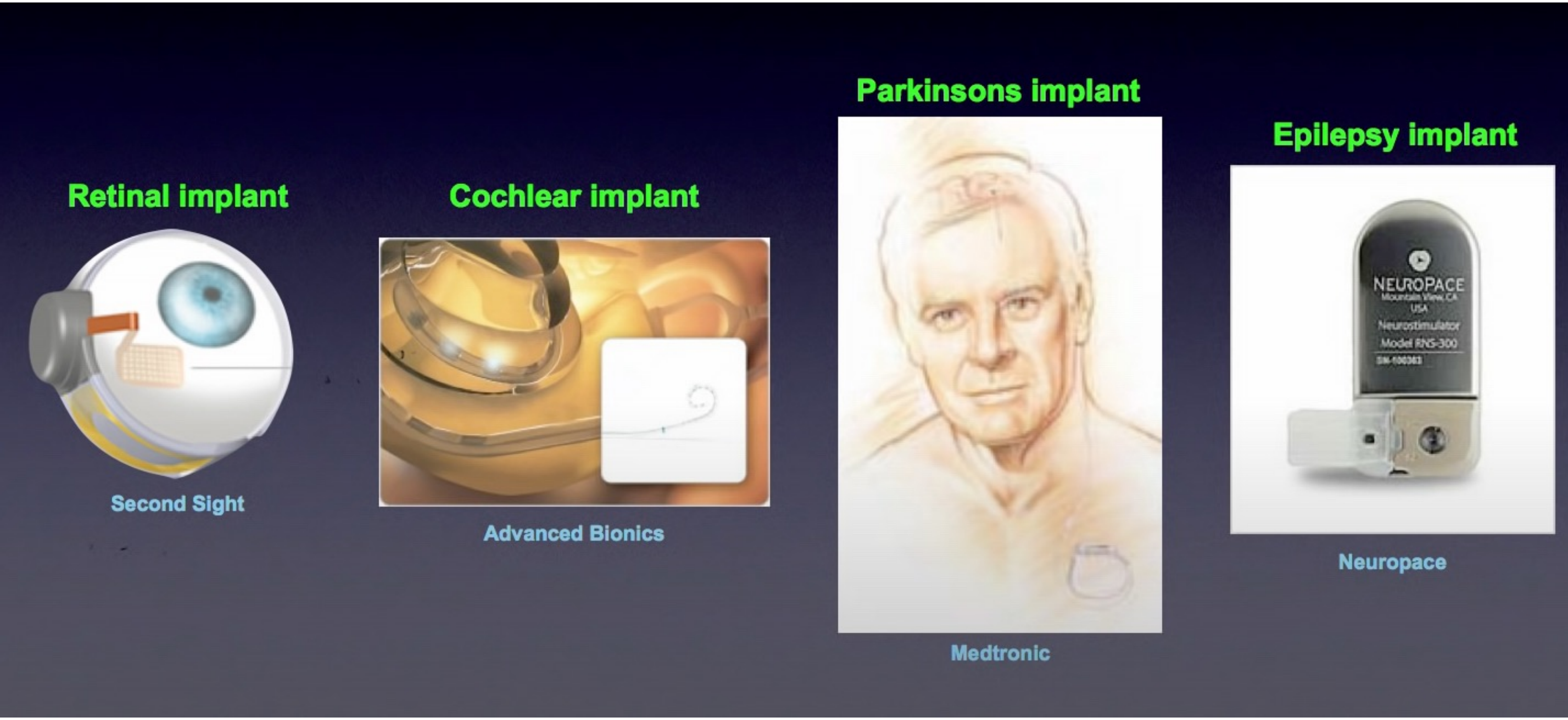
Electrophysiological brain signals



Waldert et al. (2009)



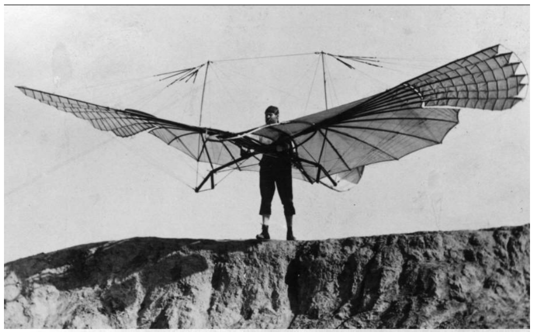
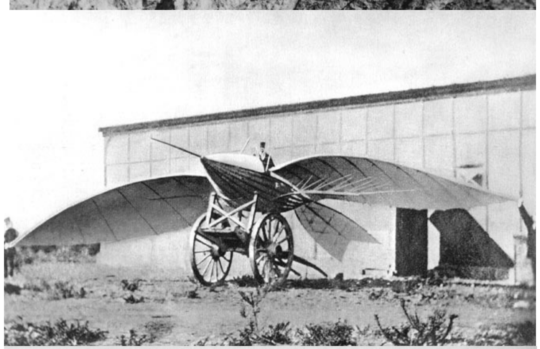
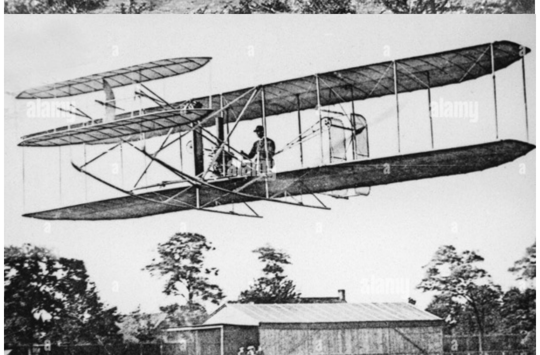
Modified from Edelman et al. (2015) Engineering



from K. Shenoy, 2013, TEDx talk

BCI examples

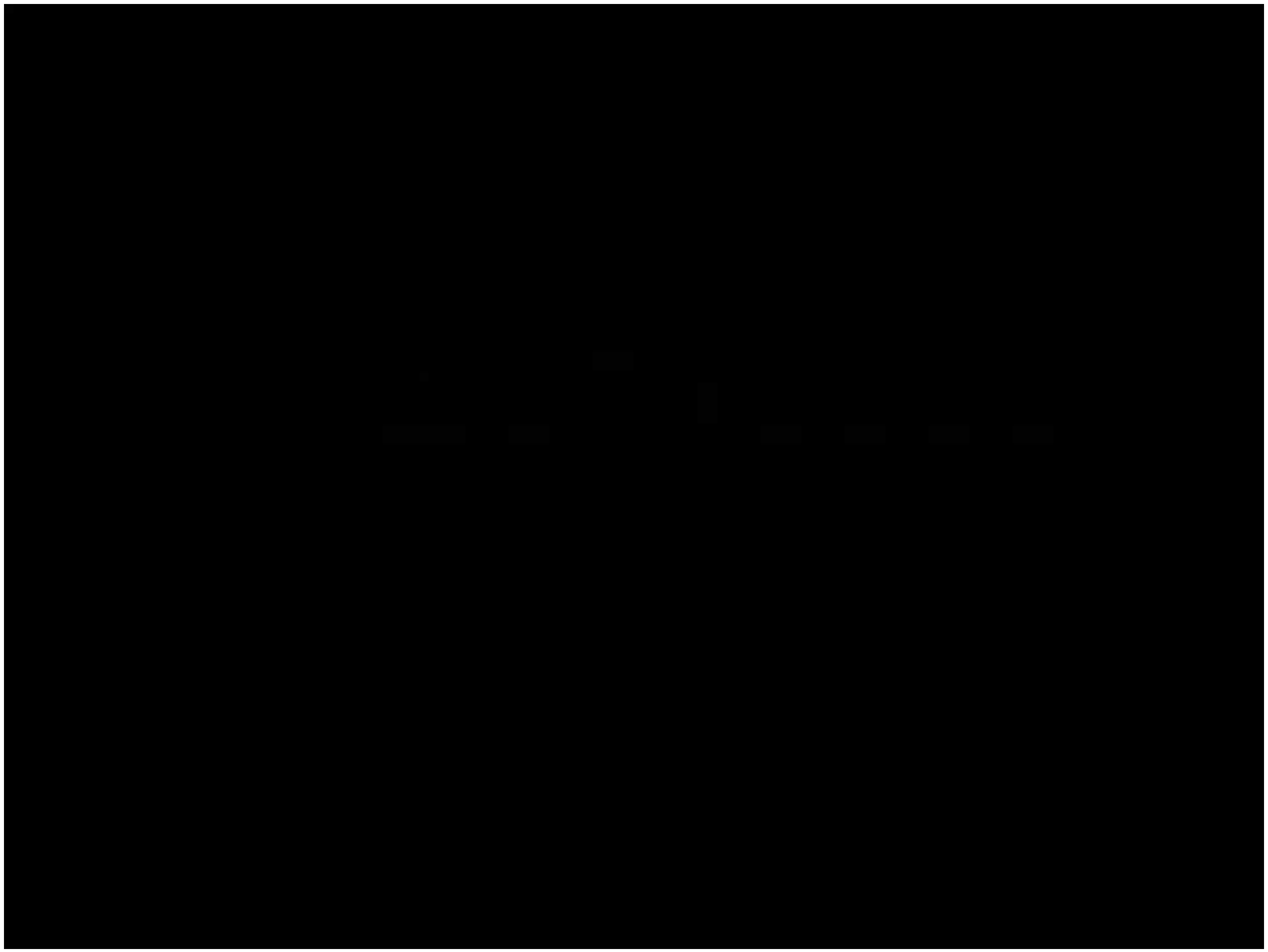
Brain-Computer Interface (BCI): we are at the beginning …


Zdroj obrázků: google (pictures)

P300 (EEG) speller: example

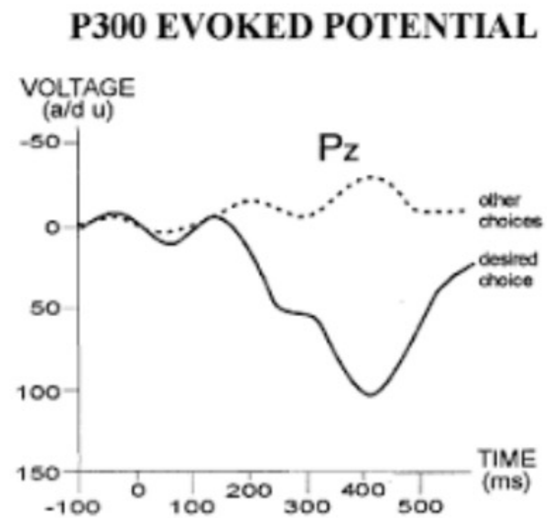
(positivity of EEG potential 300 ms after rare/unexpected stimulus)

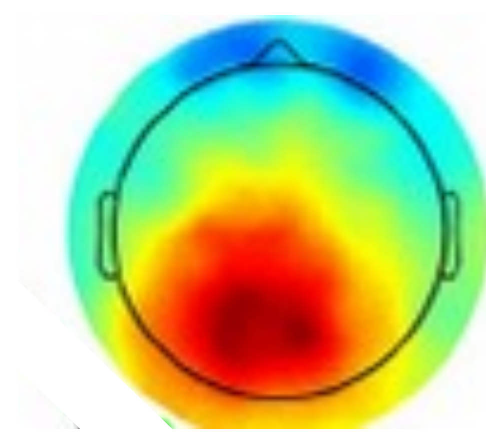


P300 (EEG) speller: principle

(positivity of EEG potential 300 ms after rare/unexpected stimulus)

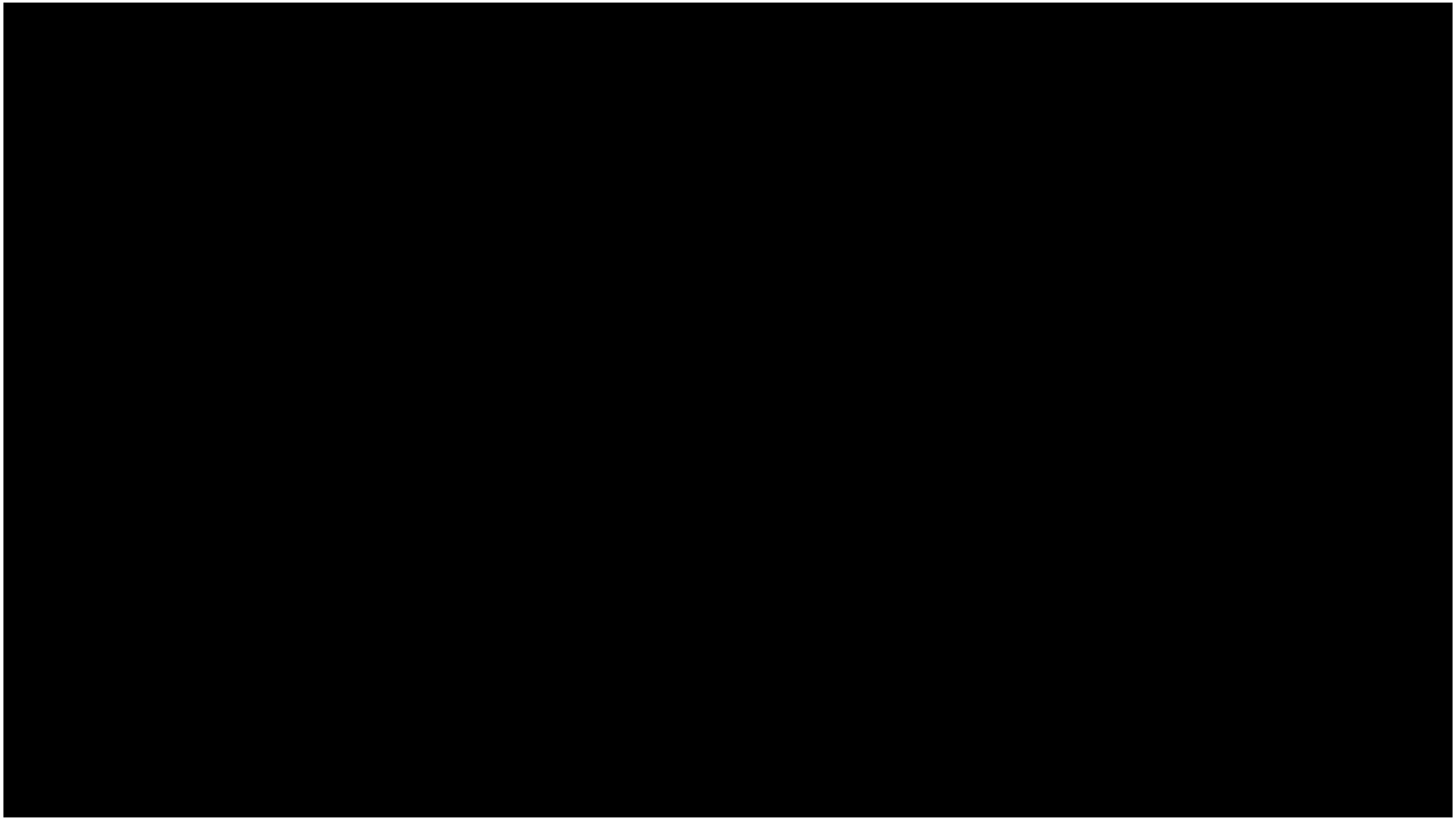
- P300 component of EEG
- Discovered in the 60s
- Low probability (surprise) stimulus
- „oddball“ paradigm
- Pronounced peak
  - positivity
  - latency: 250 - 500 ms
- Parietal area of the brain
- Applications: P300 speller
  - speed cca 10 letters/min





SSVEP (EEG) BMI: example 1

(SSVEP, steady state visual evoked potential)



SSVEP (EEG) BMI: example 2

(SSVEP, steady state visual evoked potential)

A Lower Limb Exoskeleton Control Based on Steady State Visual Evoked Potential

No-Sang Kwak, Klaus-Robert Müller and Seong-Whan Lee

Department of Brain and Cognitive Engineering, Korea University

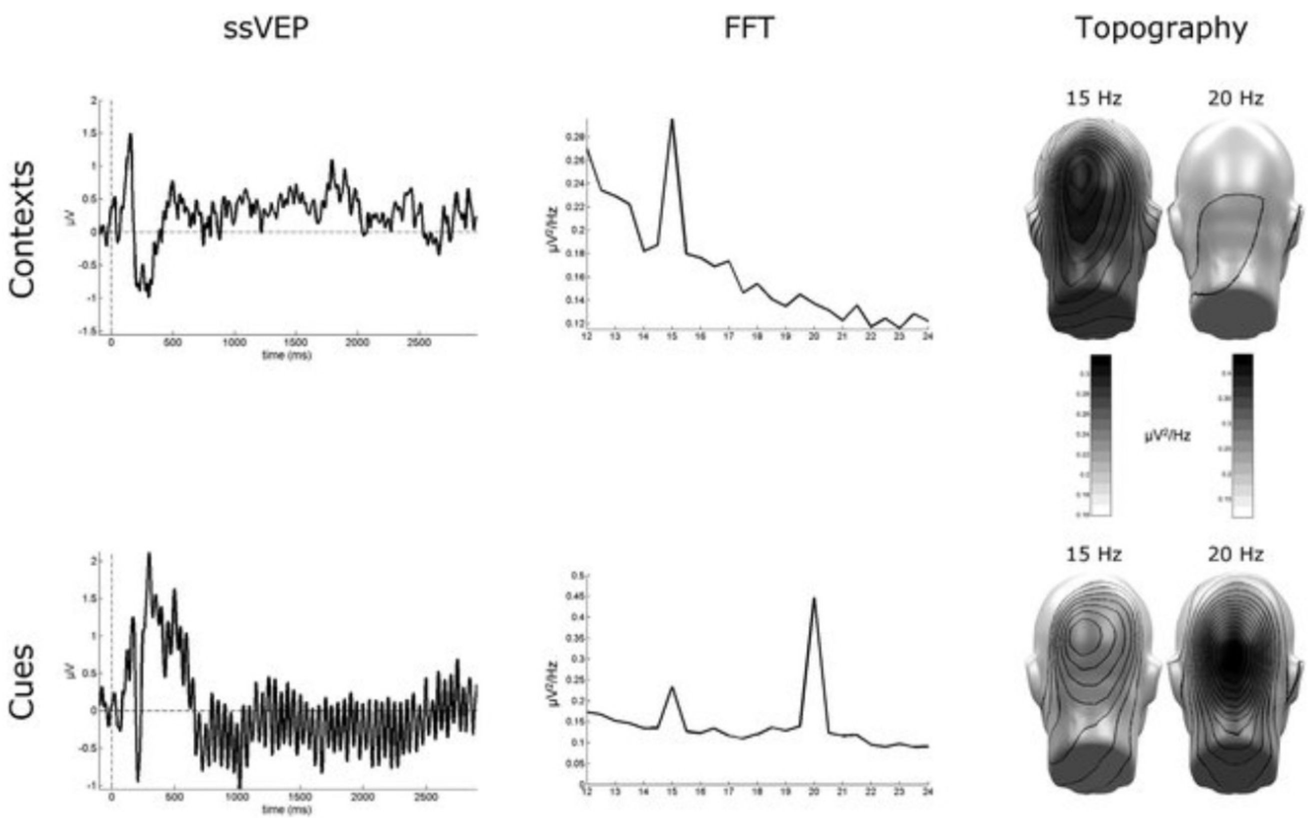
KOREA UNIVERSITY

Pattern Recognition Laboratory

SSVEP (EEG) BMI: principle

(SSVEP, steady state visual evoked potential)

- Voluntary choice of focus on stimulus
- Stimuli flickering at different frequencies
- Signal = „resonant frequency“ in visual cortex



Wieser et al. (2016) NeuroImage

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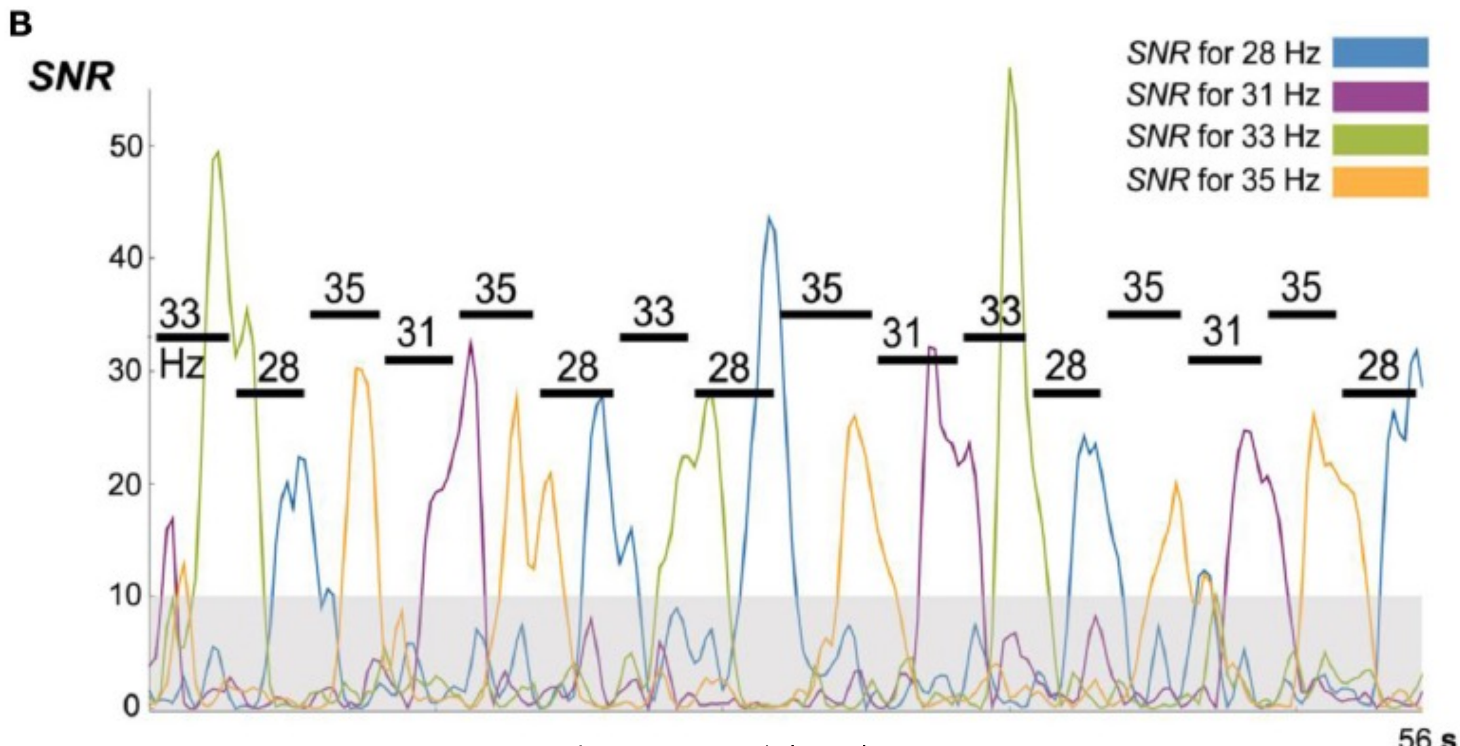


Fernandez-Vargas et al. (2013) Frontiers Neurosci

SCP (EEG) BMI

(SCP, slow cortical potentials)

LIEBER-HERR-BIRBAUMER-

HOFFENTLICH-KOMMEN-SIE-MICH-BESUCHEN,-WENN-DIESER-
BRIEF-SIE-ERREICHT-HAT-.ICH-DANKE-IHNEN-UND-IHREM-
TEAM-UND-BESONDERS-FRAU-KÜBLER-SEHR-HERZLICH,-DENN-
SIE-ALLE-HABEN-MICH-ZUM-ABC-SCHÜTZEN-GEMACHT,-DER-
OFT-DIE-RICHTIGEN-BUCHSTABEN-TRIFFT.FRAU-KÜBLER-IST-EINE-
MOTIVATIONSKÜNSTLERIN.OHNE-SIE-WÄRE-DIESER-BRIEF-NICHT-
ZUSTANDE-GEKOMMEN.-ER-MUSS-GEFEIERT-WERDEN.-DAZU-
MÖCHTE-ICH-SIE-UND-IHR-TEAM-HERZLICH-EINLADEN-.
EINE-GELEGENHEIT-FINDET-SICH-HOFFENTLICH-BALD.

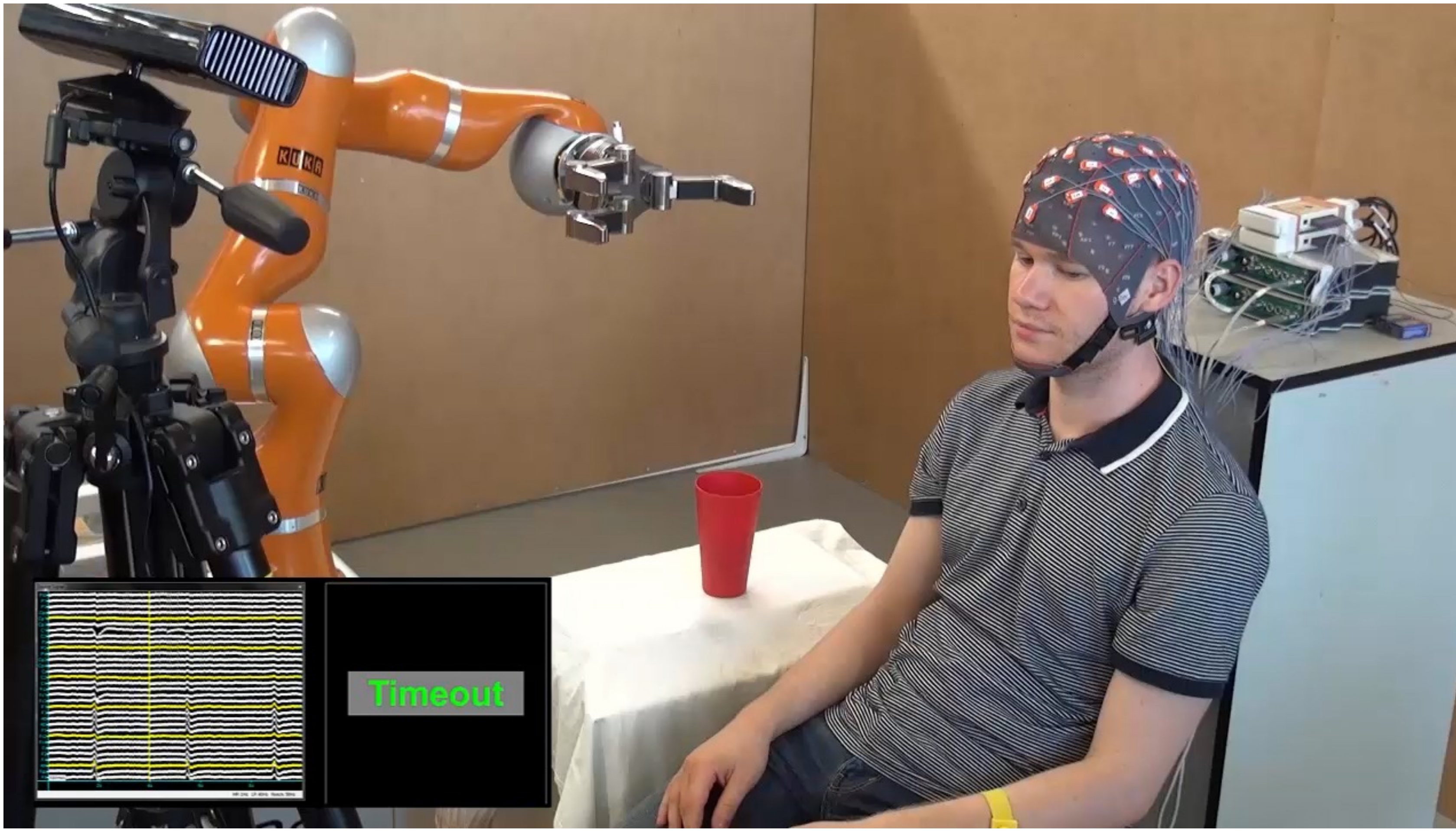
MIT-BESTEN-GRÜSSEN-
IHR-HANS-PETER-SALZMANN

Birbaumer et al. (1999) Nature

Movement-related spatial patterns, EEG BMI: example 1

(ERS / ERD, event related synchronization / desynchronization)

Movement-related spatial patterns, EEG BMI: example 2



Movement-related spatial patterns, EEG BMI: principle

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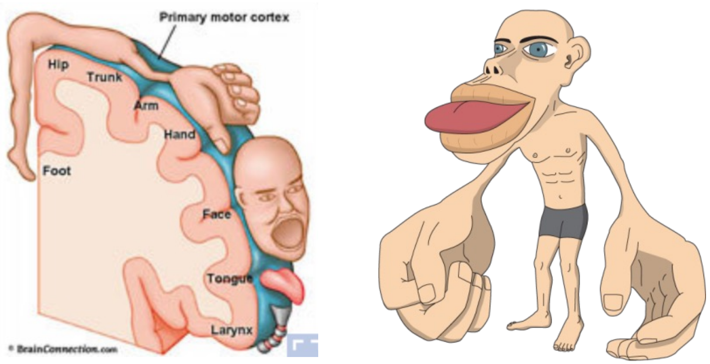
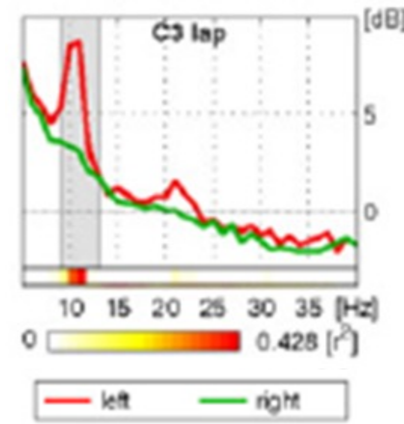
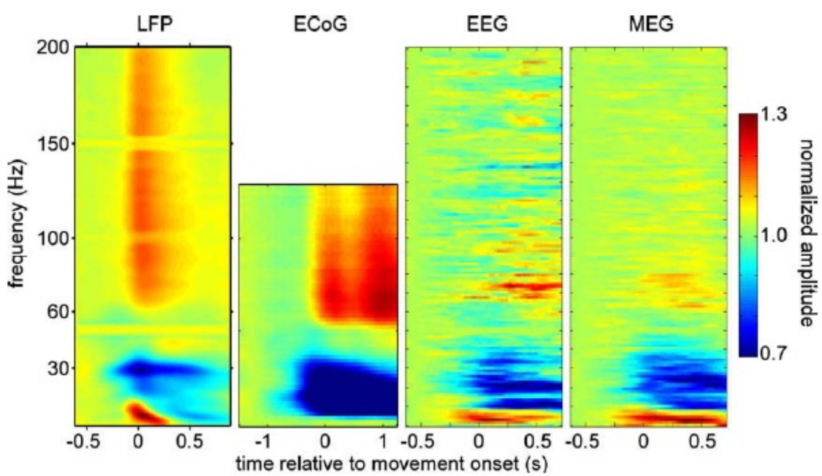
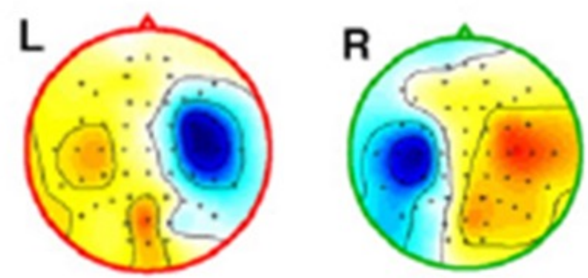


Reprezentace těla v mozku: homunkulus





Waldert et al. (2009) J Neurophysiol Paris

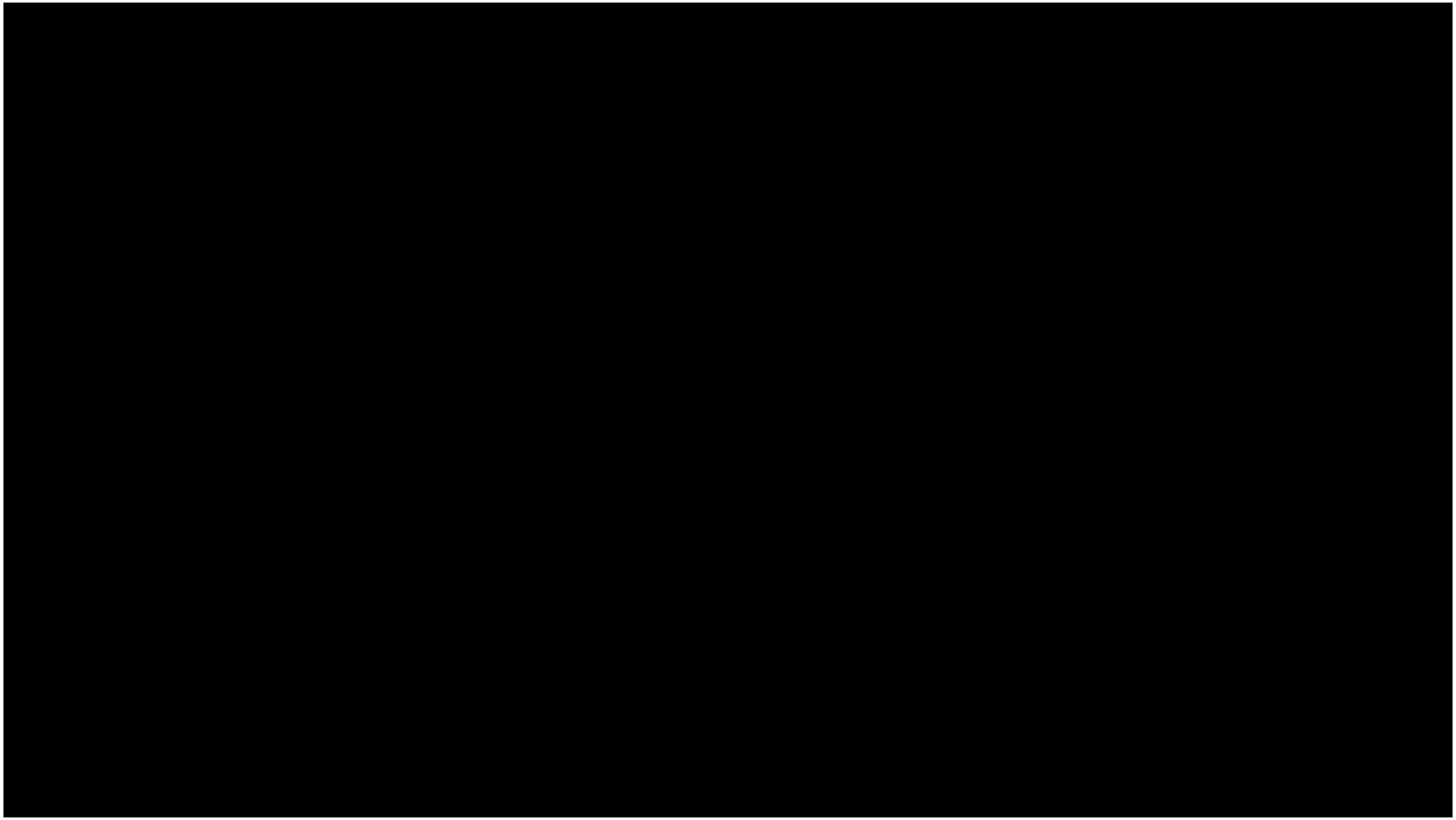


Blankertz et al. (2007) NeuroImage

Biomimetic BMI (single neurons): example 1

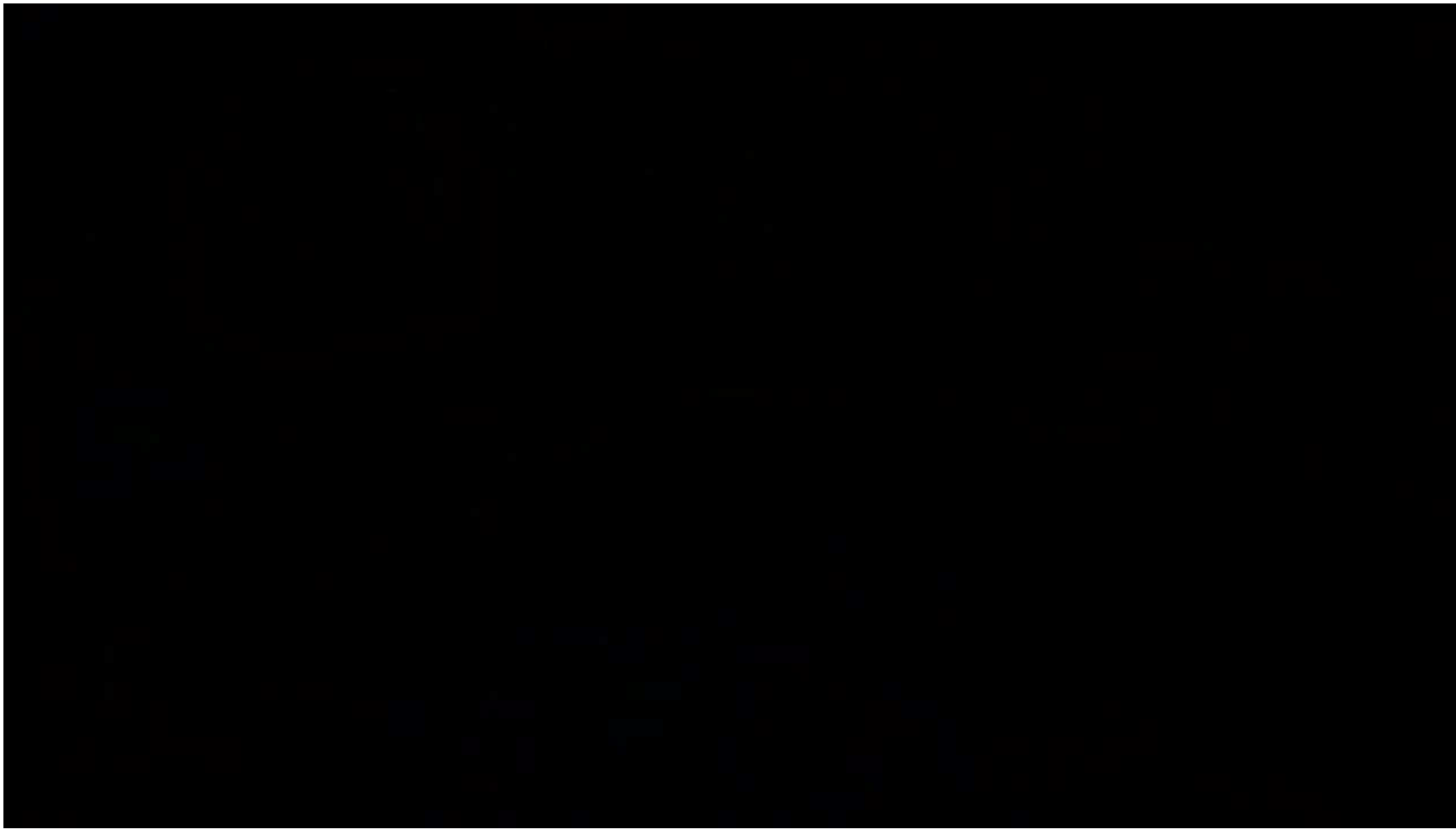
zdroj: youtube (Brain machine interface: monkey controls 4DOF robot arm)

Biomimetic BMI (single neurons): example 2



Hochberg et al. (2006) Nature

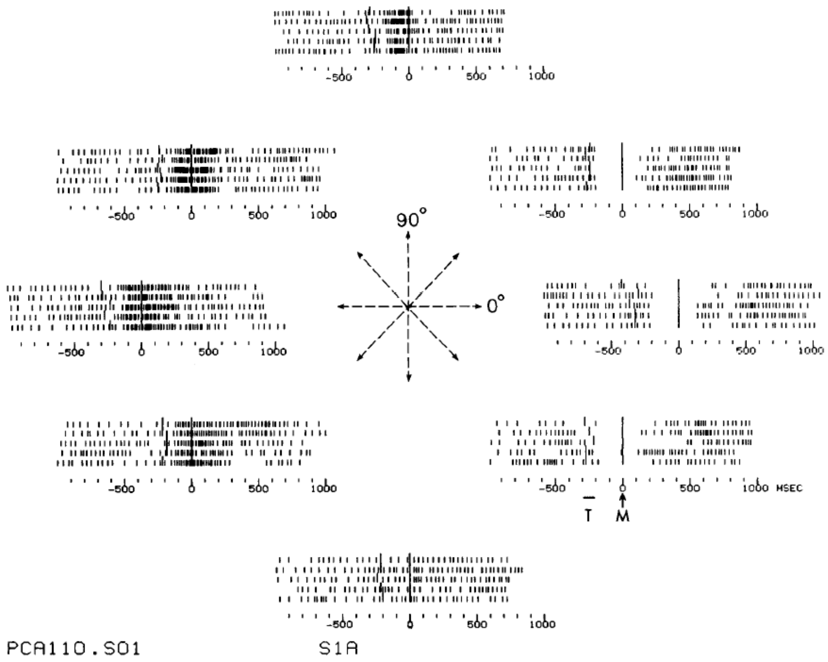
Biomimetic BMI (single neurons): example 3



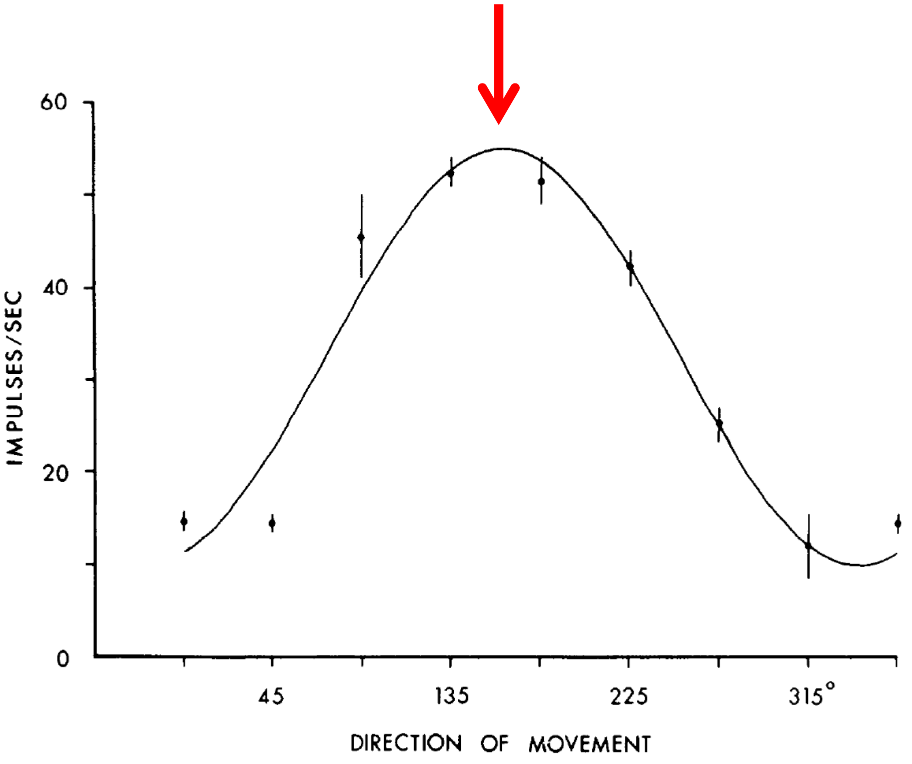
Collinger et al. (2014) Lancet

Biomimetic BMI (single neurons): principle

Directional „cosine tuning“ of motor cortex neurons

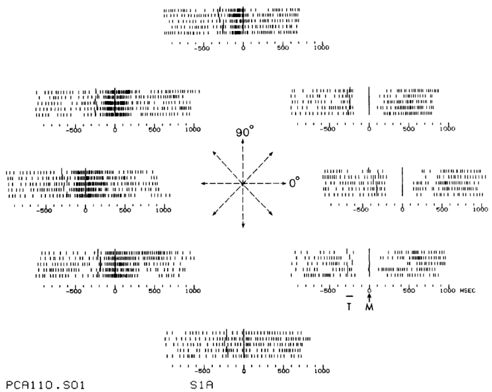


Preferred direction of discharge

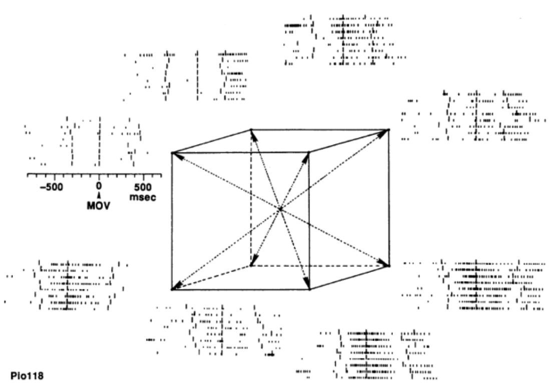


Georgopoulos et al. (1982) J Neurosci

Biomimetic BMI (single neurons): principle

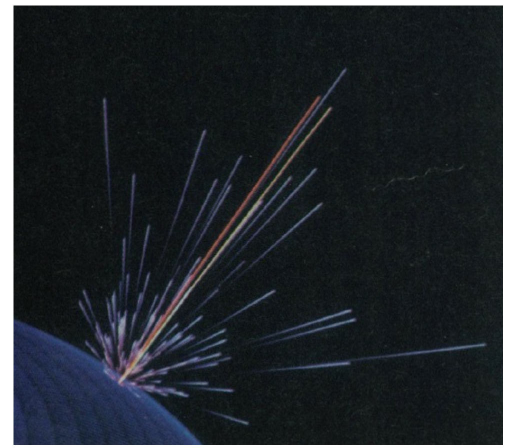


Georgopoulos et al. (1982) J Neurosci



Georgopoulos et al. (1986) Science

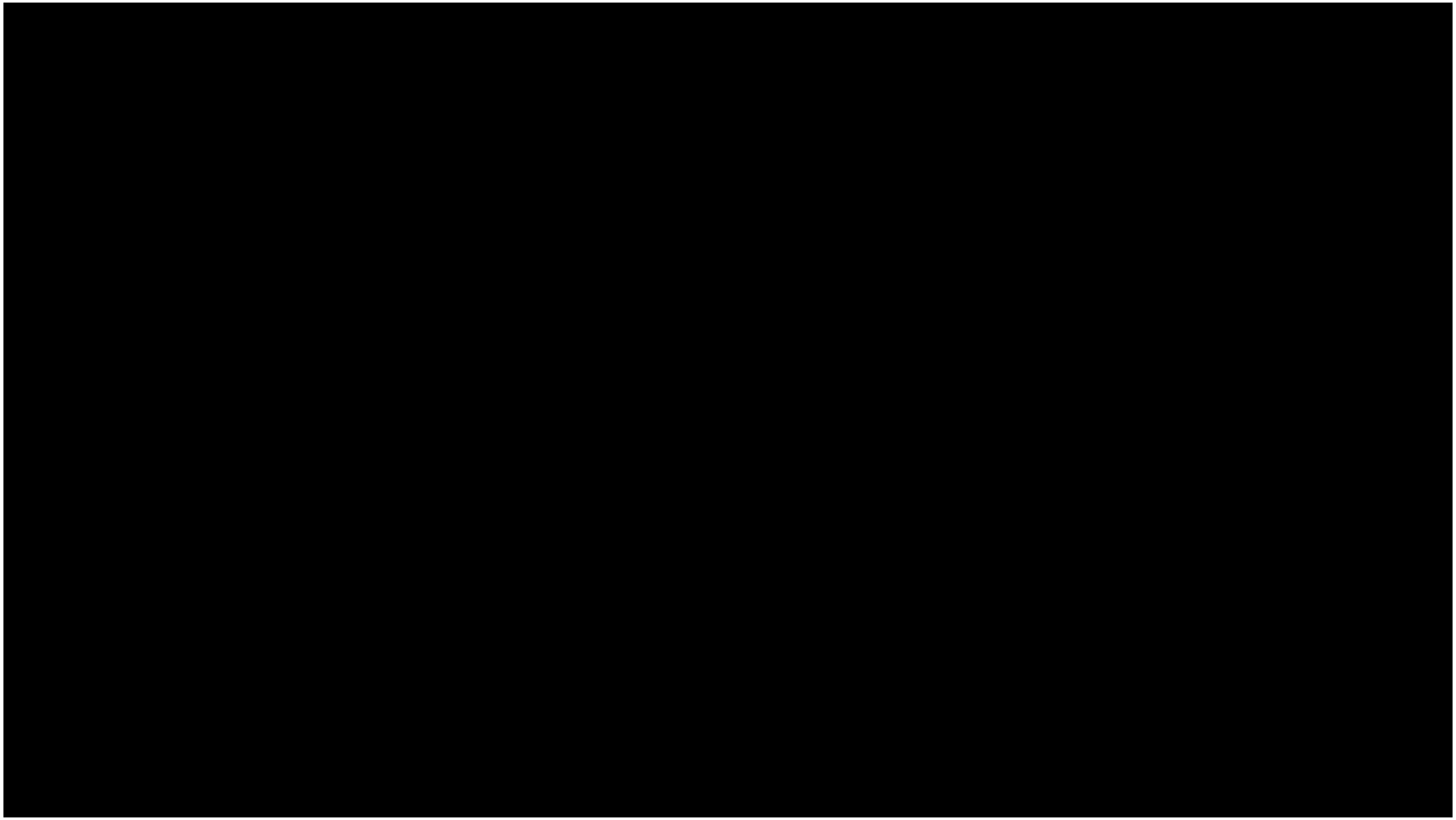
Decoding model for movement direction
= sum of neuronal population along preferred directions



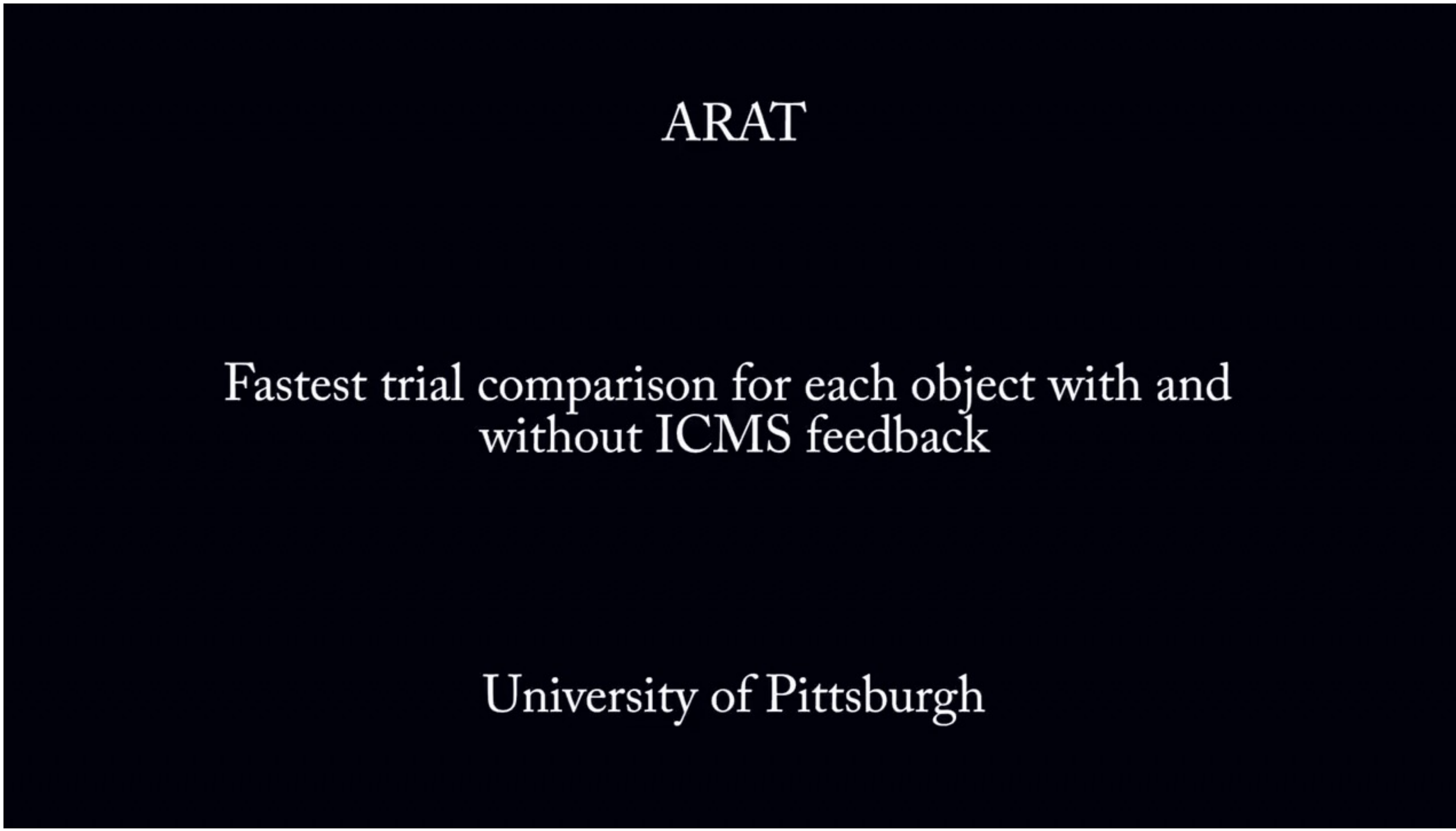
$$\boldsymbol{P}(\boldsymbol{M}) = \sum_{n=1}^{N} r_n(\boldsymbol{M})\boldsymbol{\Phi}_n$$

$\boldsymbol{P}$ ~ predicted movement direction
$\boldsymbol{M}$ ~ intended movement direction
r_n ~ discharge of *n*-th neuron
$\boldsymbol{\Phi}_n$ ~ preferred direction of *n*-th neuron
N ~ number of neurons

BMI (single neurons): with sense of touch – example 1

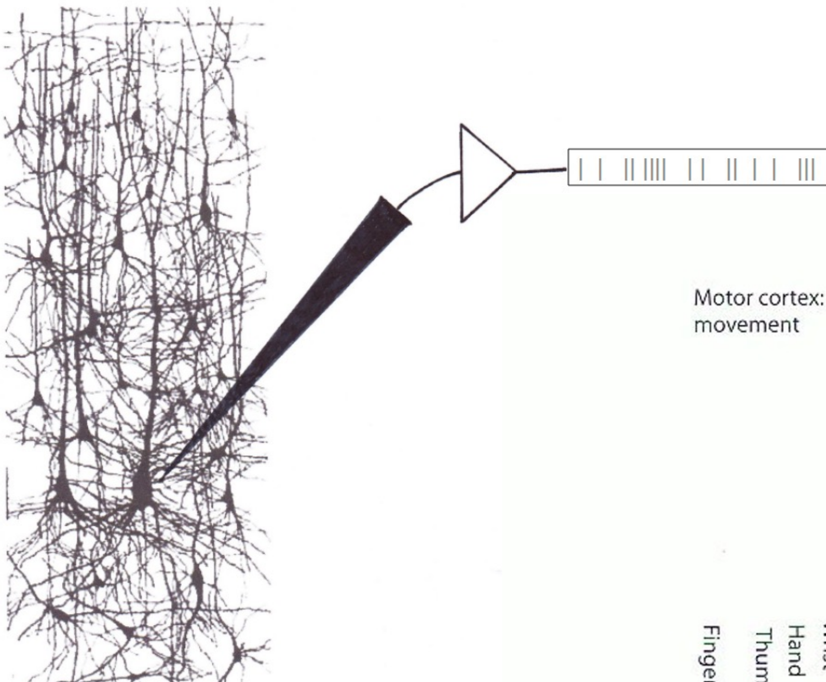


BMI (single neurons): with sense of touch – example 2

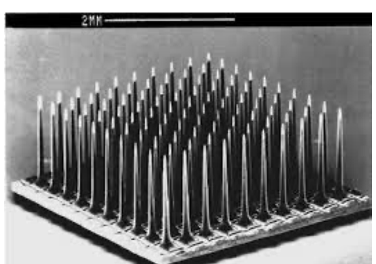


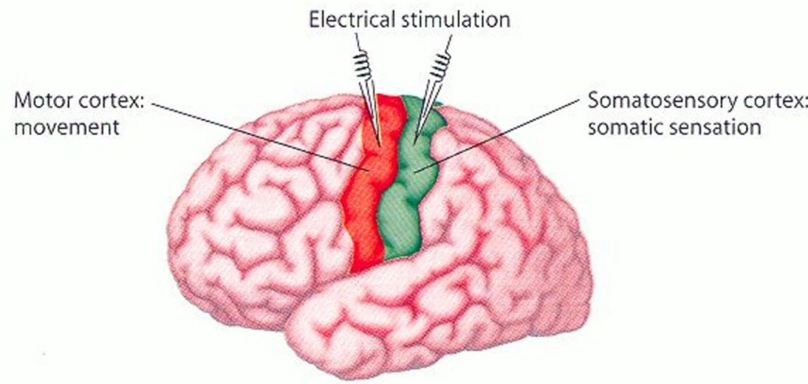
Flesher et al. (2021) Science

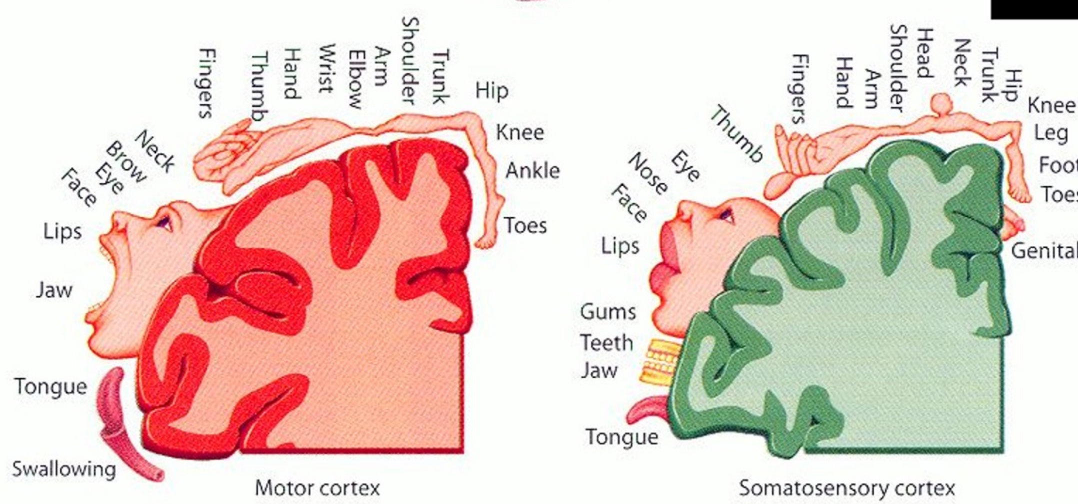
BMI (single neurons): with sense of touch



Modified from
Elston (2003)







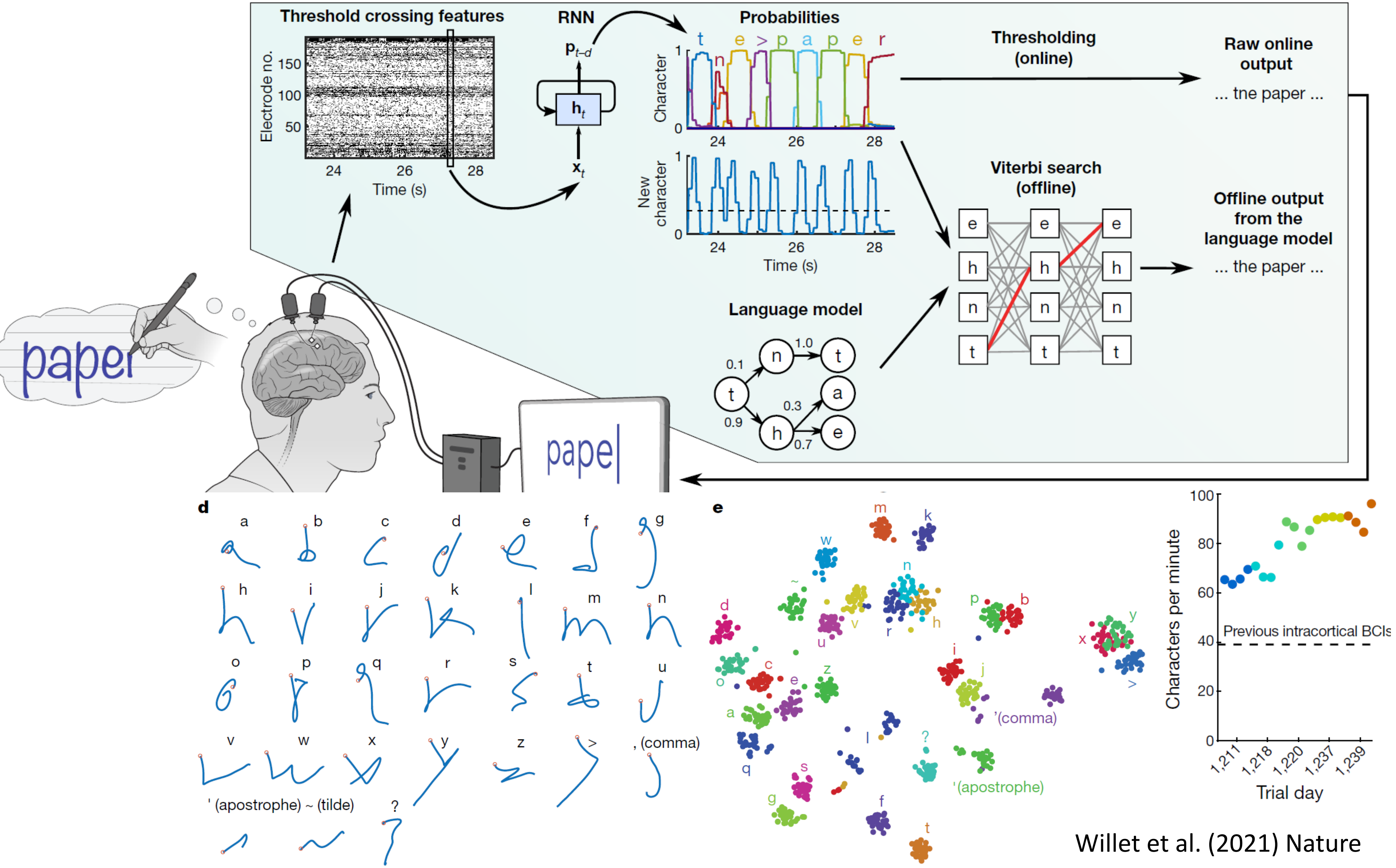
*motorický a sensitivní homunkulus jsou si velmi podobní (velké tváře, jazyk, ruce; motorický homunkulus nemá genitál)

Neuls a Botek: Základy neurofyziologie

BCI (single neurons): text writing example

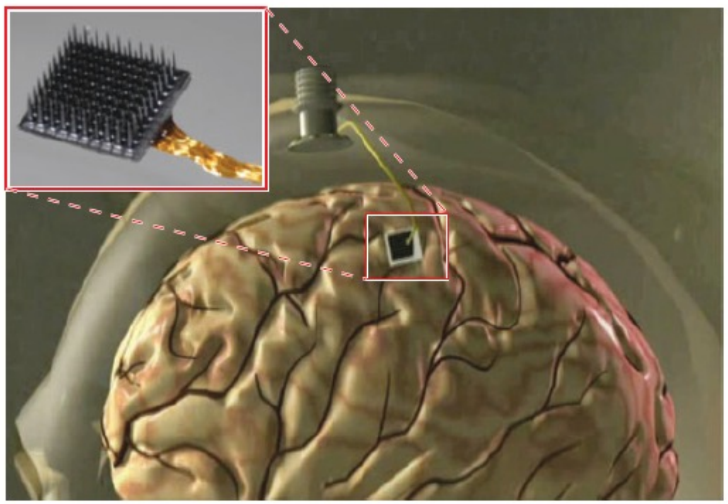
From YouTube (Krishna Shenoy: Brain-to-text communication via imagined handwriting-Tencent WE Summit 2021)

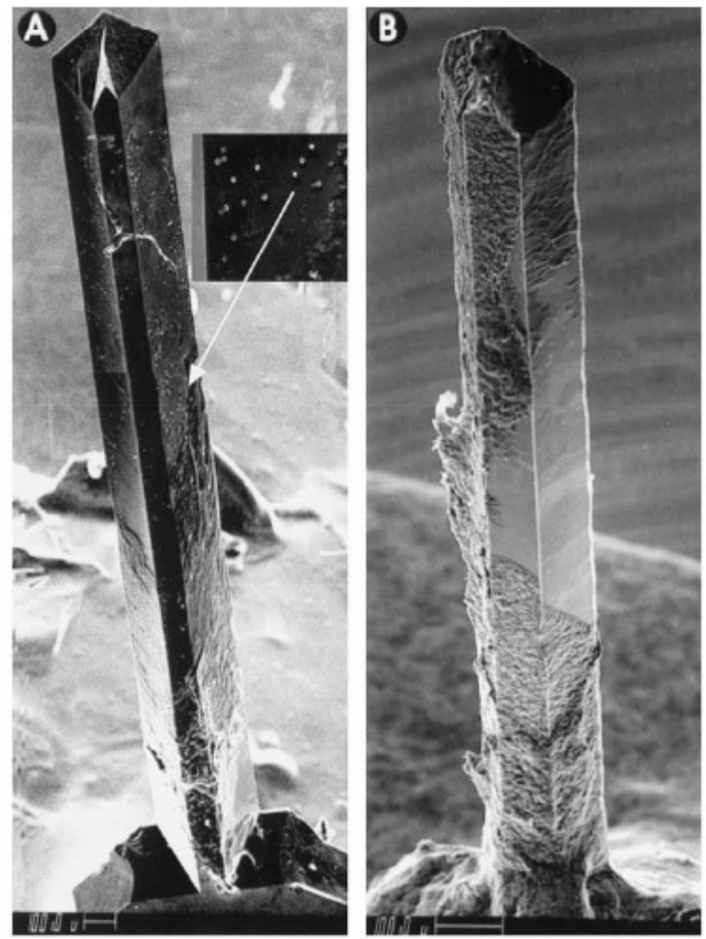
BCI (single neurons): text writing principle



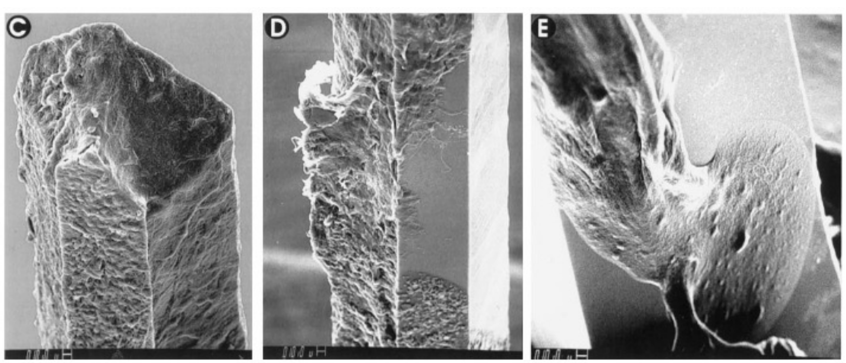
Willet et al. (2021) Nature

Problem: myelinization of micro-electrodes





after 2 and 6 weeks after implantation

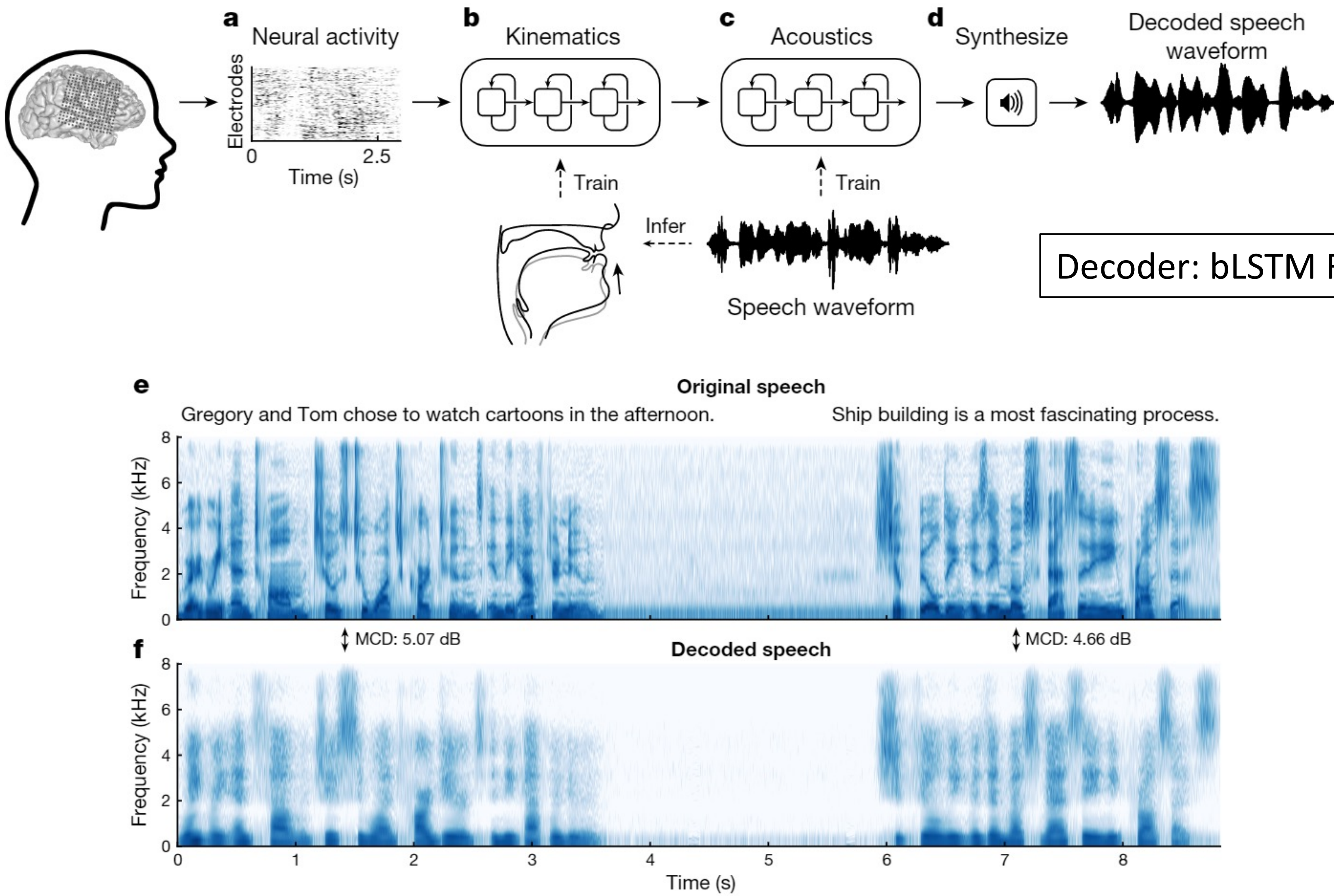


Turner et al. (1999) Experimental neurology

BMI: Speech synthesis of spoken sentences from ECoG

Anumanchipalli et al. (2019) Nature

BMI: Speech synthesis of spoken sentences from ECoG



Decoder: bLSTM RNN

Anumanchipalli et al. (2019) Nature

BMI: Speech synthesis of spoken sentences from ECoG

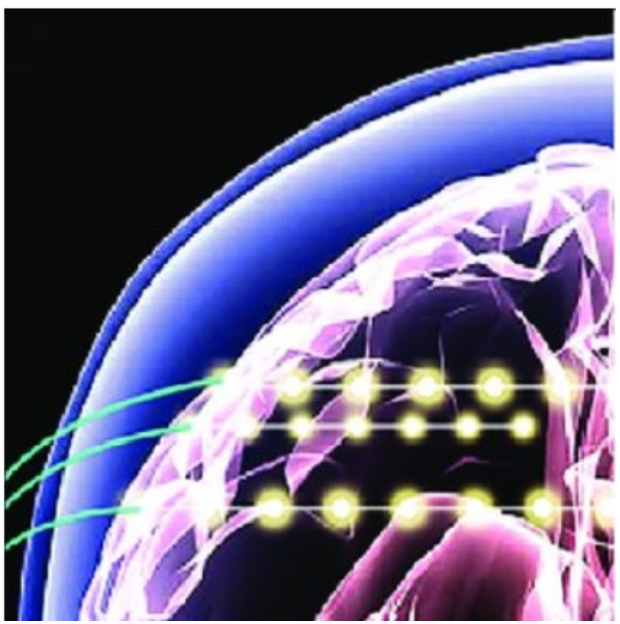
- We designed a recurrent neural network that decoded cortical signals with an explicit intermediate representation of the articulatory dynamics to synthesize audible speech.
- **STAGE 1:** a bLSTM RNN decodes **articulatory kinematic features** from continuous neural activity (Fig. 1a, b)
  - high-gamma amplitude envelope and low frequency component
  - from vSMC, STG, IFG
- **STAGE 2:** a separate bLSTM, decodes **acoustic features** (pitch, mel-frequency cepstral coefficients (MFCCs), ...) from the decoded articulatory features (Fig. 1c)
- **The audio signal** is then synthesized from the decoded acoustic features (Fig. 1d).
- To integrate the two stages of the decoder, stage 2 (articulation-to-acoustics) was trained directly on output of stage 1 (brain-to-articulation) so that it not only learns the transformation from kinematics to sound, but also corrects articulatory estimation errors made in stage 1.

„Our“ BMI research
(Prof. Tonio Ball, Freiburg)

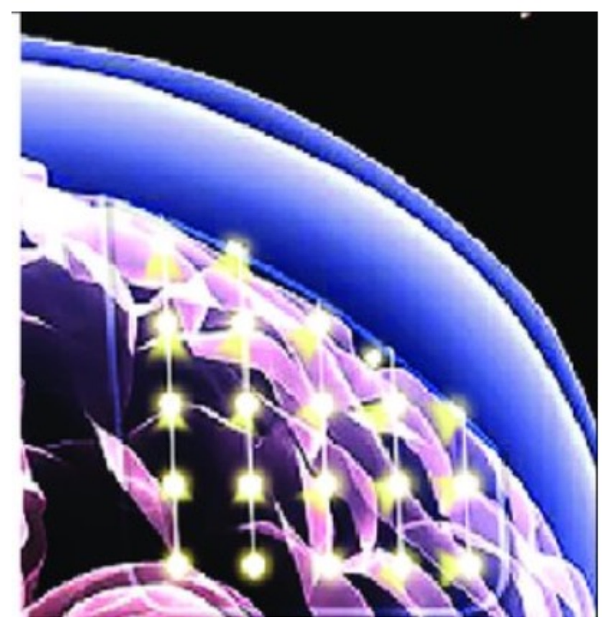
Intracranial EEG (iEEG)

- Invasive
- Signal quality is superior to scalp EEG
- Patients with epilepsy
- Cognitive experiments during video-EEG monitoration

sEEG (stereo-EEG)

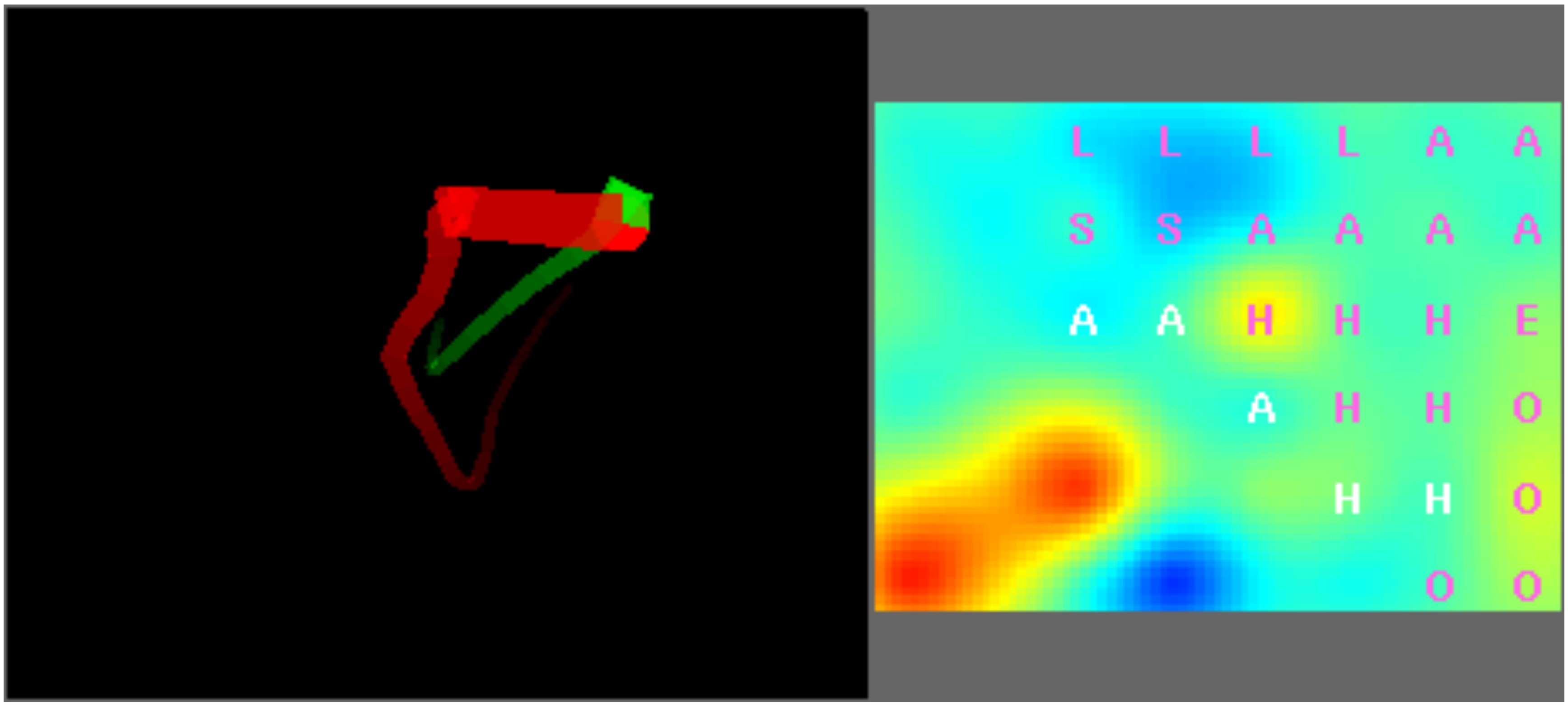


ECoG (electrocorticography)



Biomimetic BMI (ECoG): example 1

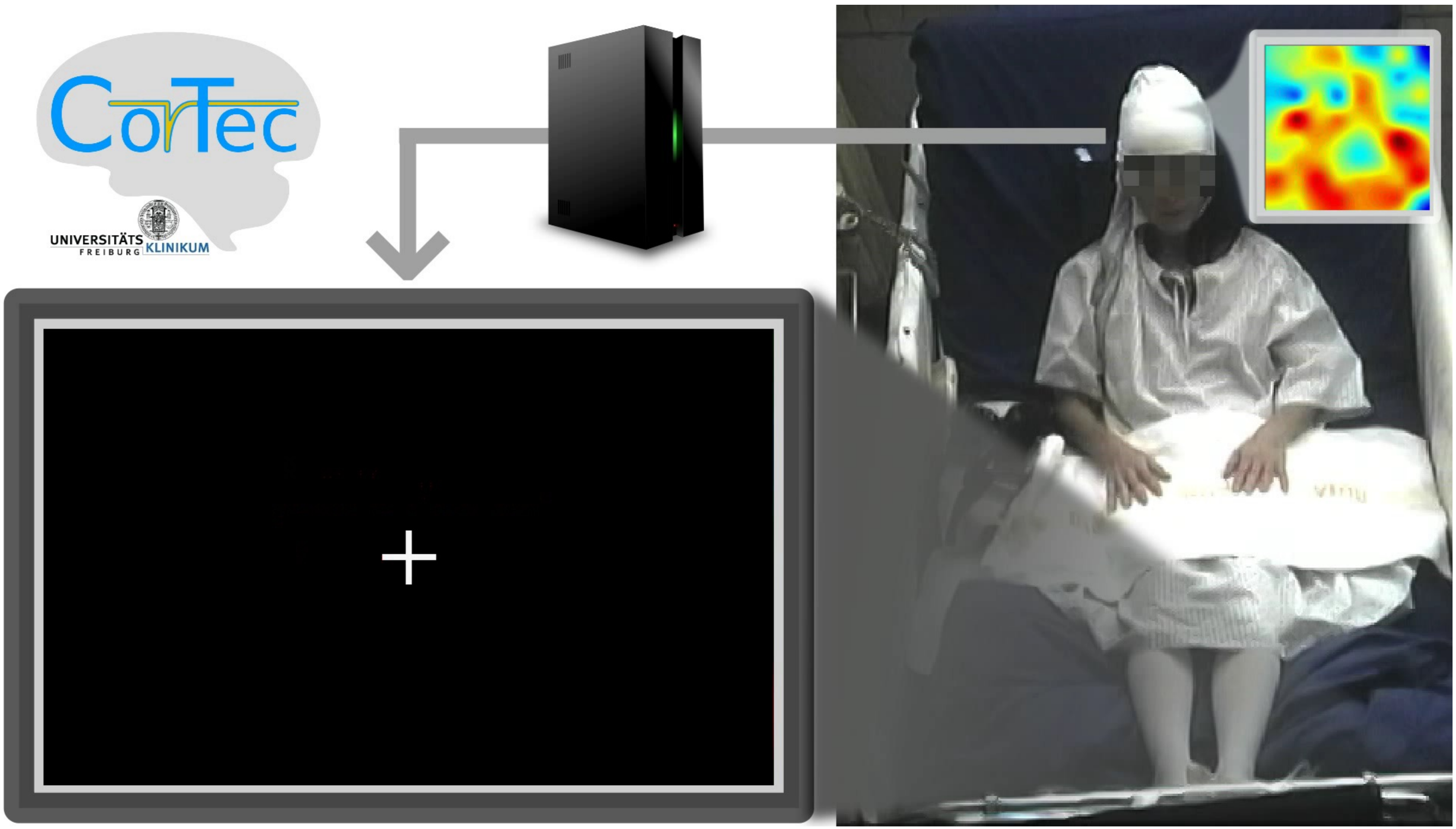
(electrocorticography)



Pistohl et al. (2008) J Neurosci Methods

Biomimetic BMI (ECoG): example 2

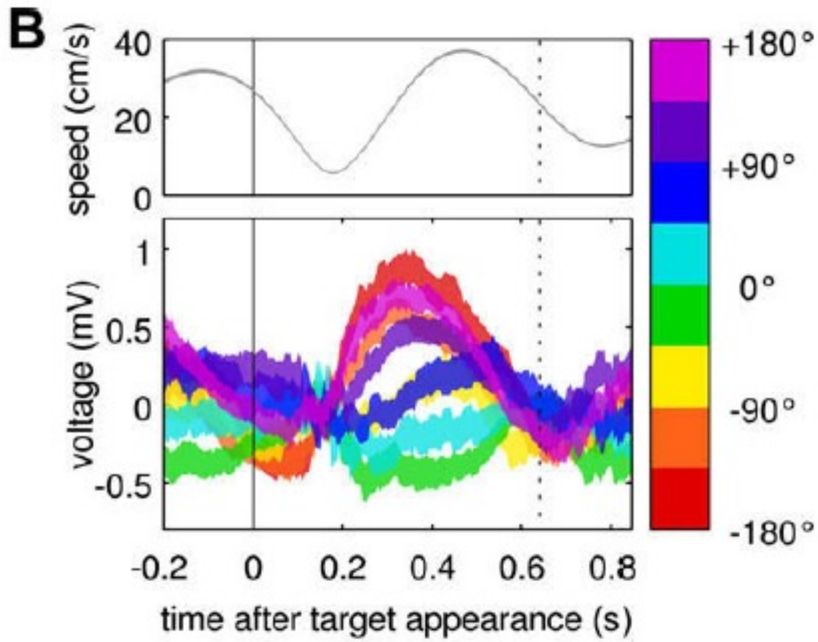
(electrocorticography)



Milekovic et al. (2012) J Neural Eng

Biomimetic BMI (ECoG): principle

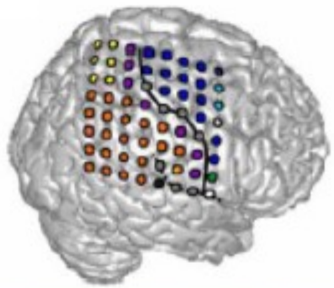
(electrocorticography)

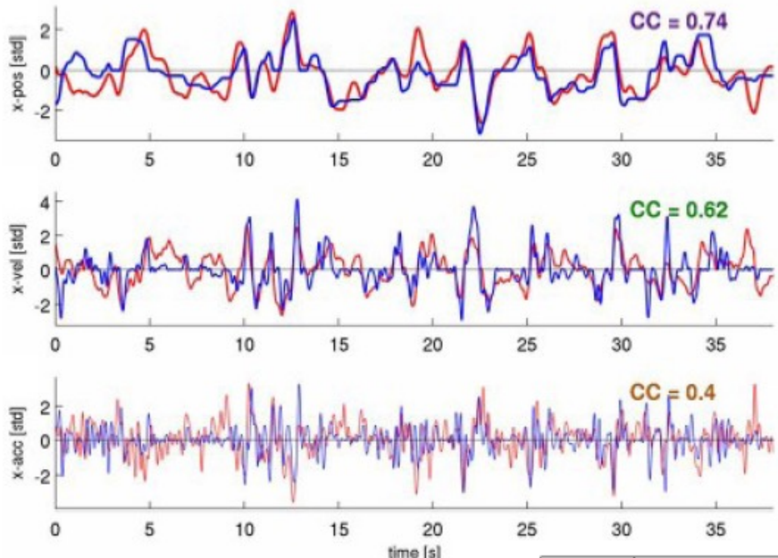


- Decoder: example 1
  - Kalman filter
- Decoder: example 2
  - LDA (linear discriminant analysis)

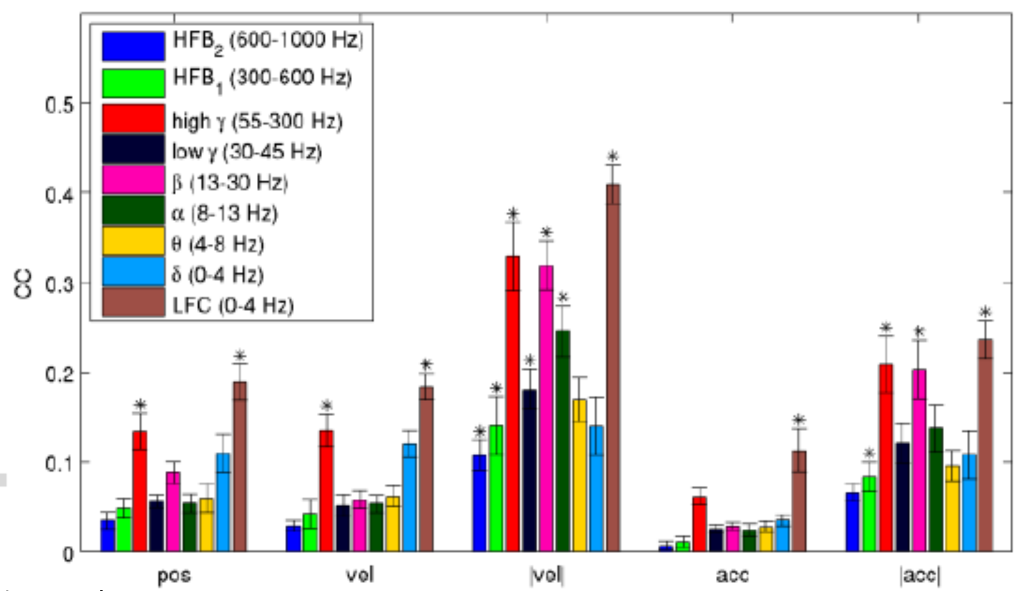
Waldert et al. (2009) J Neurophysiol Paris

Biomimetic BMI (ECoG): "my own" results



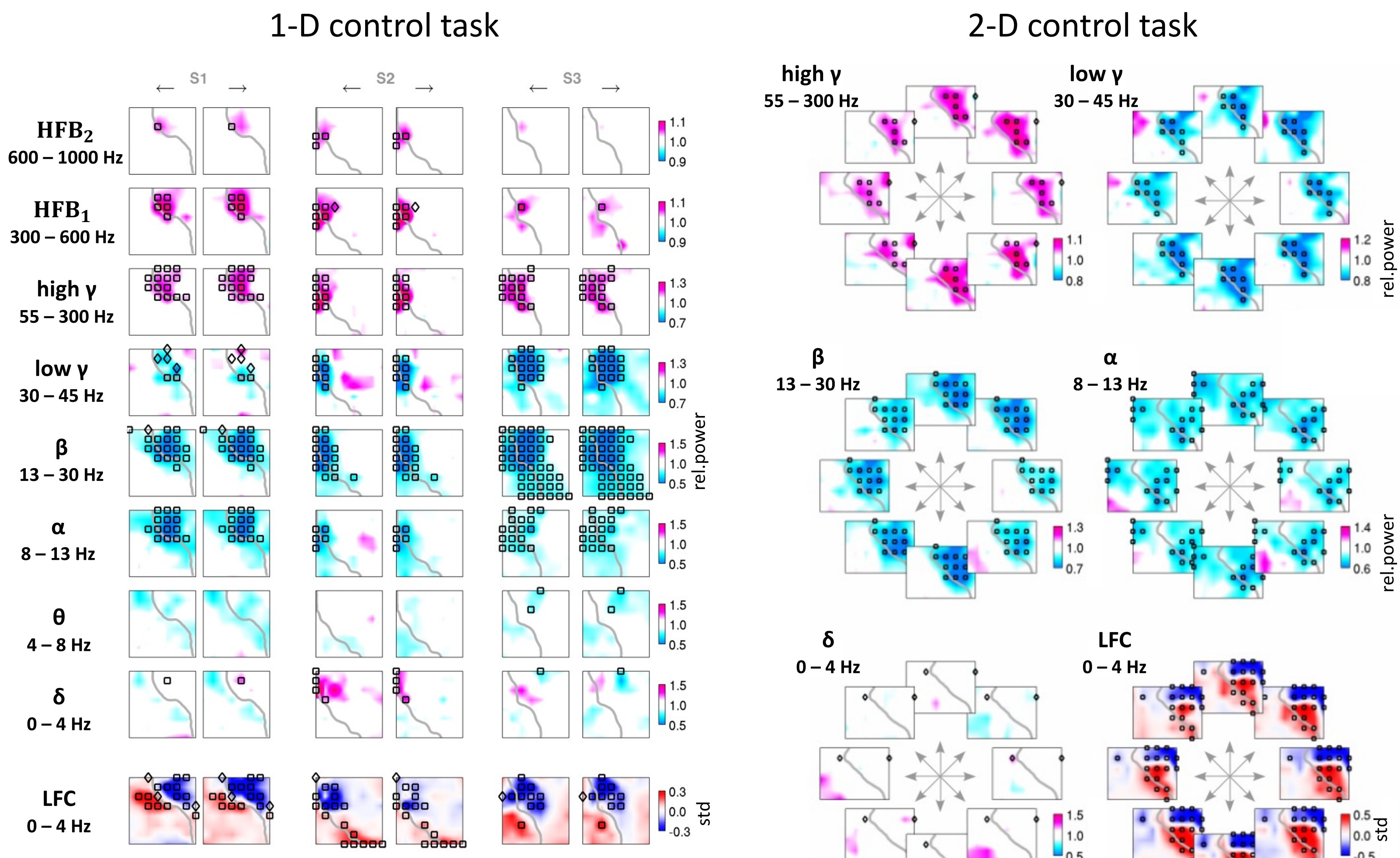


- Decoder:
  - multiple linear regression



Hammer et al. (2013) Frontiers Neurosci

Tuning of ECoG to different movement directions



Hammer et al. (2016) Cereb Cortex

Movement speed correlates with motor-cortical activation.

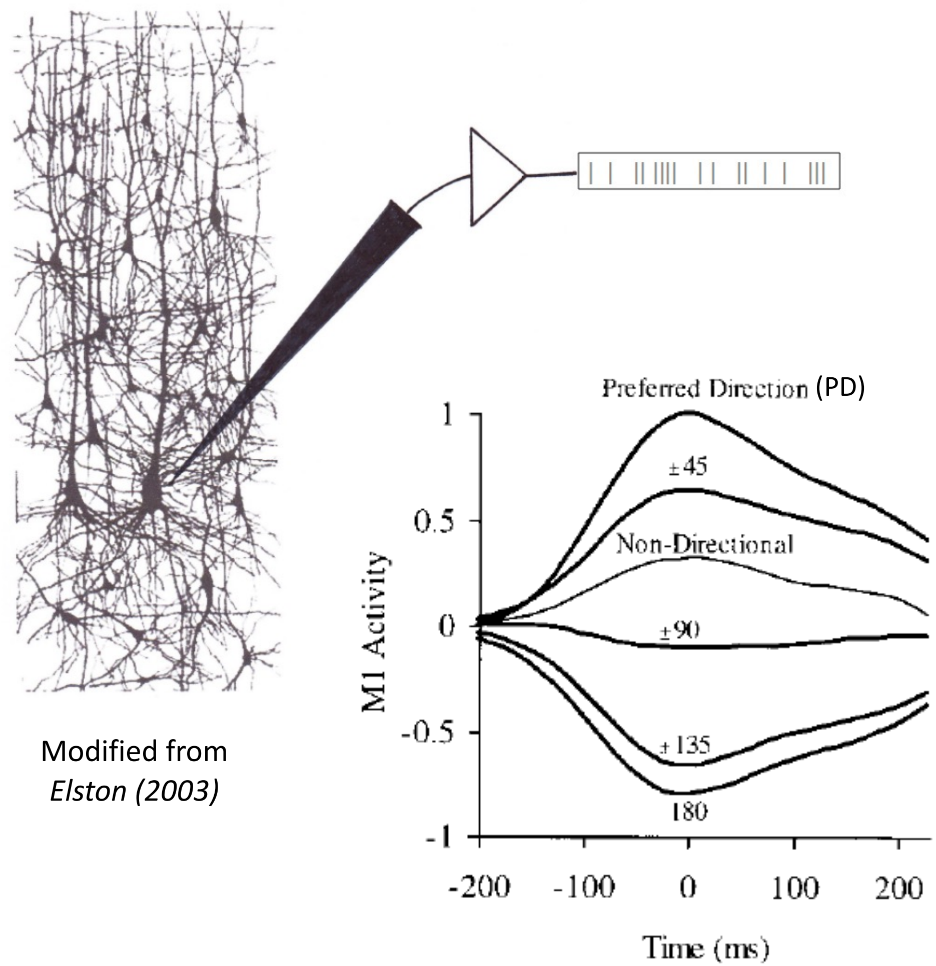
Velocity tuning of single-unit activity (SUA)

- ECoG
  - strong speed tuning
  - weak directional tuning

- SUA
  - strong directional tuning

    (e.g. *Georgopolous et al. 1982*)
  - weak speed tuning

    (e.g. *Moran and Schwartz, 1999*)



Modified from *Elston (2003)*

Moran and Schwartz (1999)

Model of neuronal population activity

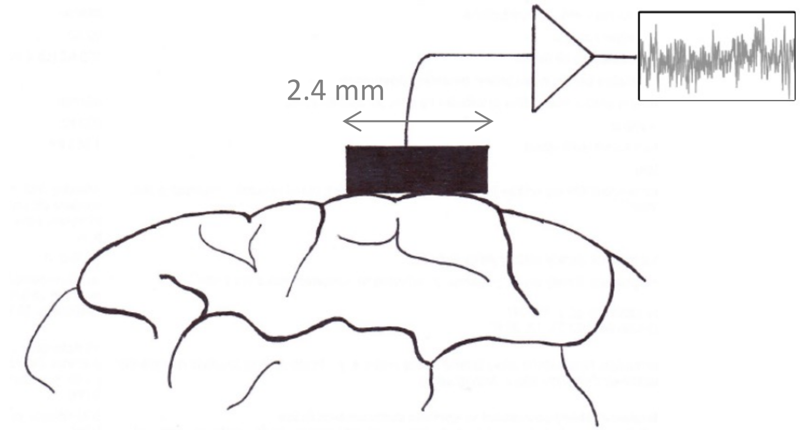
- Mimics the activity of a recorded ECoG electrode

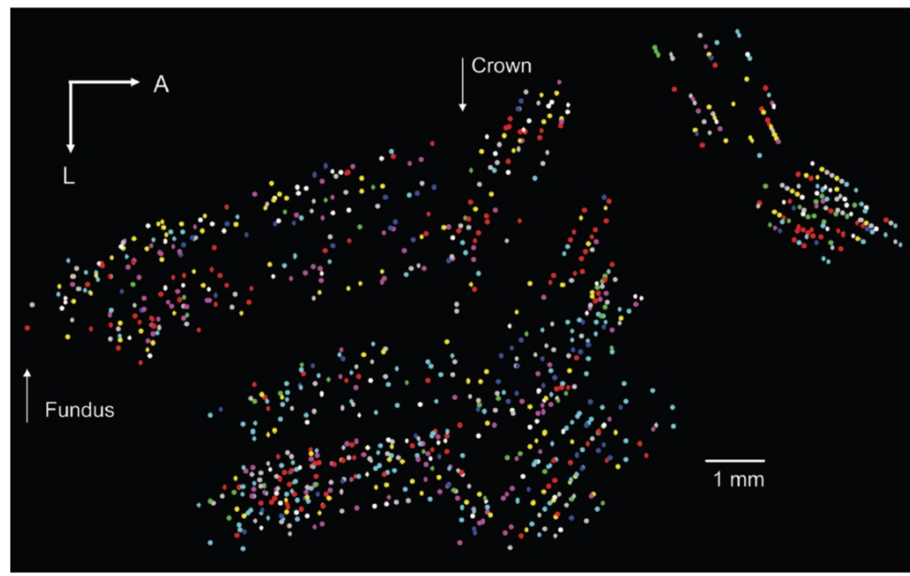
- Assumptions
  - spatial sum of firing rates of underlying SUA

    (*Waldert et al., 2009)*
  - random distribution of PDs on a mm scale

    (e.g. *Georgopoulos et al., 2007*)
  - discharge activity as a function of movement velocity

    (*Moran and Schwartz, 1999*)





Georgopoulos et al., 2007

Model of neuronal population activity

SNR of directional and speed tuning

$$P_N(\varphi, s) = \sum_{n=1}^{N} d_n(\varphi, s)$$

$$= \sum_{n=1}^{N} [S_n \cdot s + V_n \cdot \mathrm{s} \cdot \cos(\varphi - PD_n) + \varepsilon_n]$$

P_N ~ population activity of *N* neurons
d_n ~ discharge of *n*-th neuron
φ ~ direction
s ~ speed

Moran and Schwartz (1999)

Model of neuronal population activity

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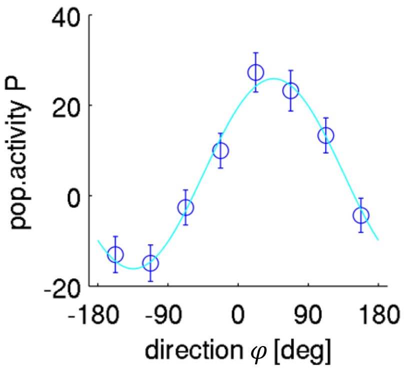
s ~ speed

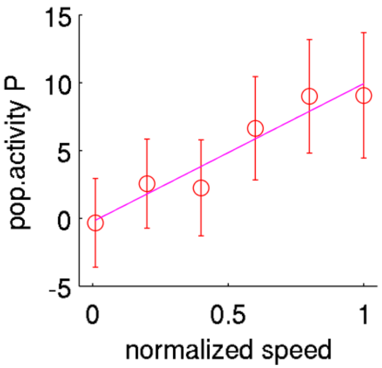
Moran and Schwartz (1999)

Example $P_N(\varphi, s)$
N = 1000 neurons

Directional tuning



Speed tuning



$$SNR = \frac{var_{tuning}}{var_{trials}}$$

Model of neuronal population activity

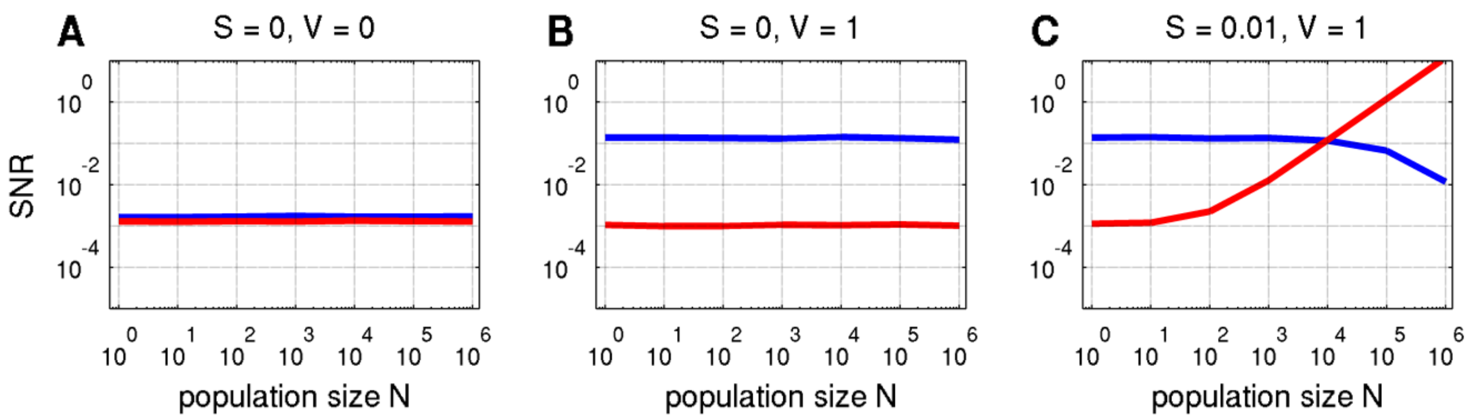
SNR of directional and speed tuning

$$P_N(\varphi, s) = \sum_{n=1}^{N} d_n(\varphi, s)$$

$$= \sum_{n=1}^{N} [S_n \cdot s + V_n \cdot s \cdot \cos(\varphi - PD_n) + \varepsilon_n]$$

$P_N \sim$ population activity of N neurons
$d_n \sim$ discharge of n-th neuron
$\varphi \sim$ direction
$s \sim$ speed

Moran and Schwartz (1999)



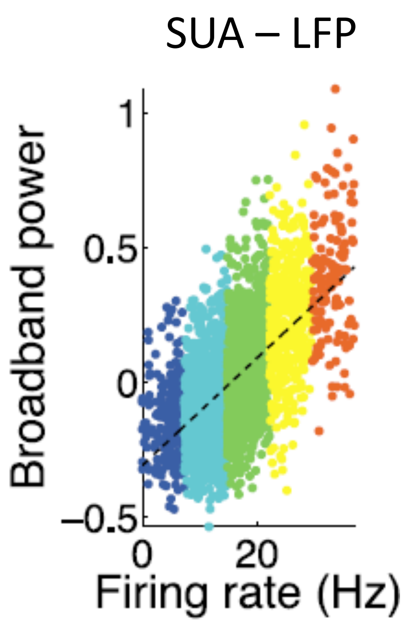
Hammer et al. (2016)

directional tuning
speed tuning

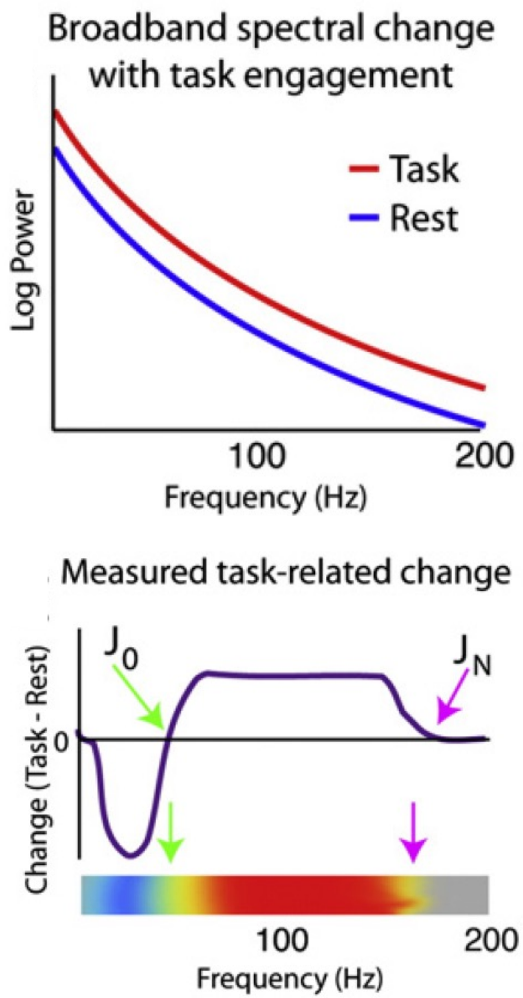
Neuronal population activity
is consistent with robust
speed representation.

Neuronal population activity
increases with speed.

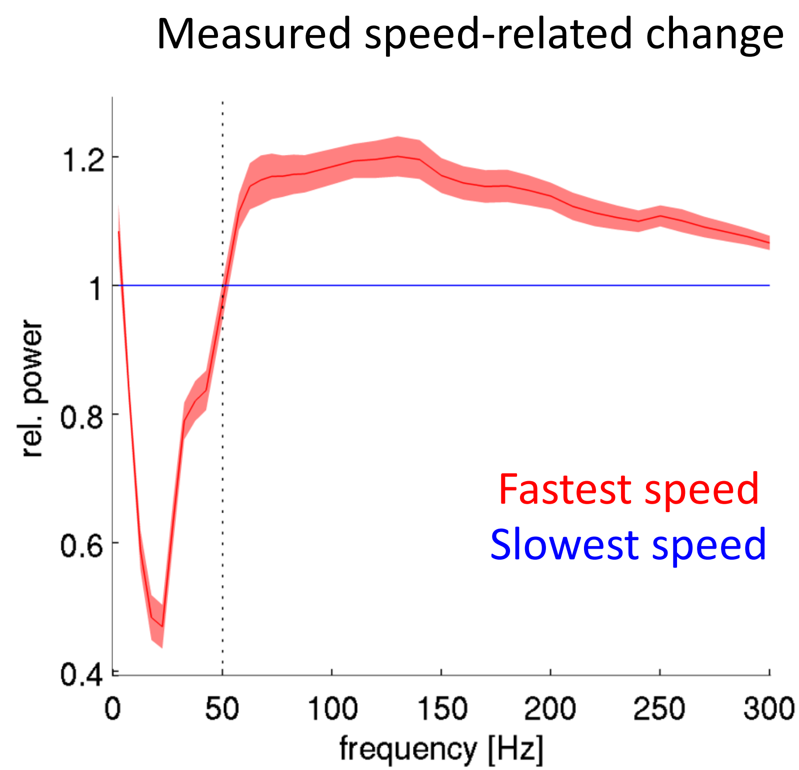
Why do we see speed-related power increase up to 1 kHz ?



Manning et al. (2009)



Miller et al. (2014)

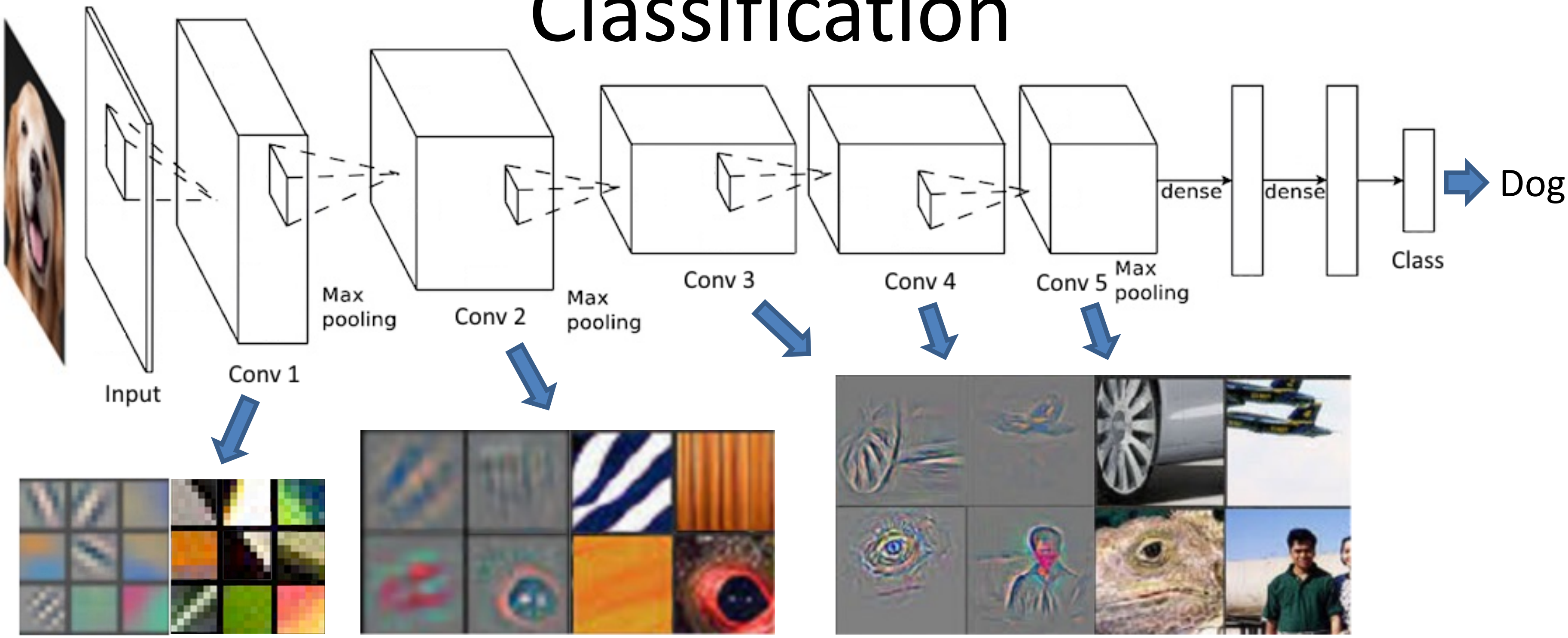


Hammer et al. (2016)

Deep learning in BMI

- Deep artificial neural networks
  - CNN (convolutional neural networks)
  - RNN (recurrent neural networks), ...
- Recent breakthroughs in hard machine learning problems
  - Computer vision
  - Language processing
  - ...
- + Super-human performance
- + Capable of *end-to-end* learning
- + No need for feature engineering
- - Particularly dark „black box“ algorithm
- - Requires large datasets
- Useful in BMI research ?

Intermediate Representations in ConvNets Trained for Image Classification



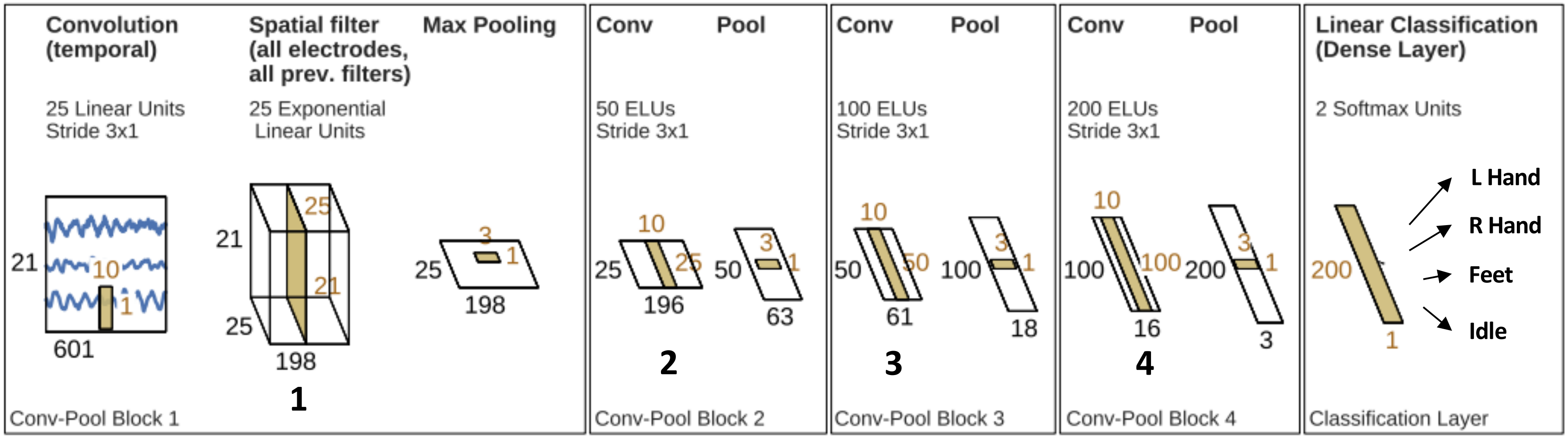
Edges Contrasts

Textures Basic shapes

Complex object parts

Krizhevsky et al. 2012
Zeiler et al. 2013

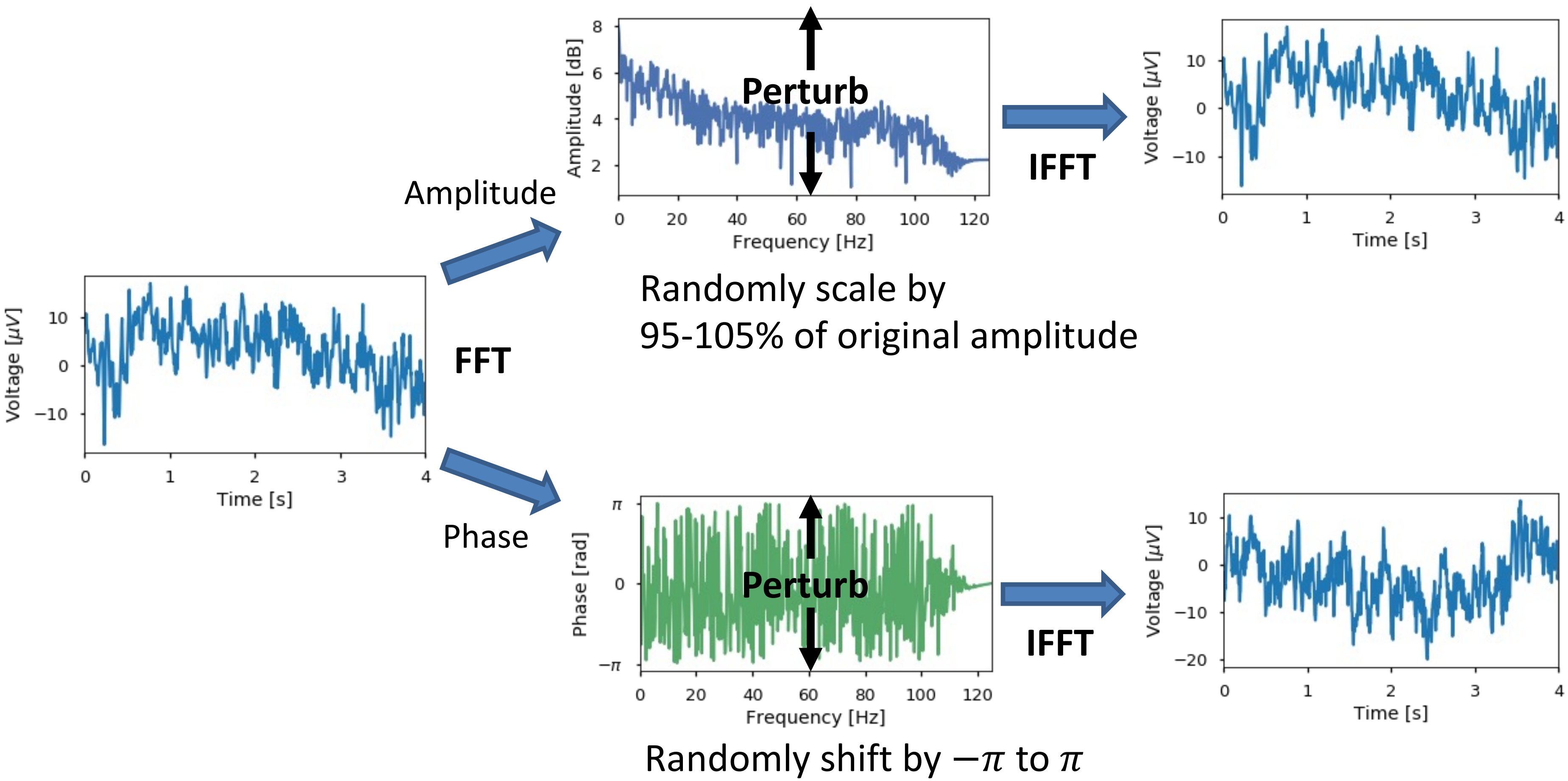
Deep4: CNN for EEG (classification problem)



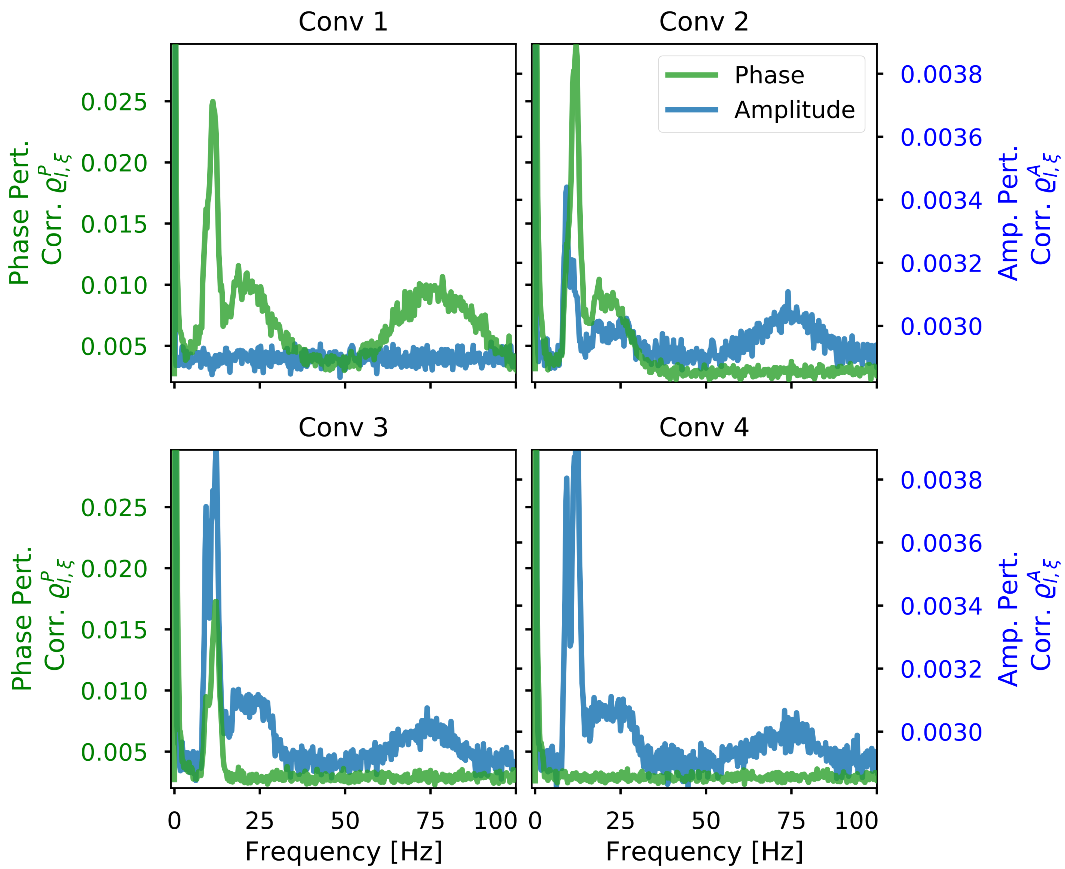
Schirrmeister et al. 2017

Investigate learned filters of convolutional layers: **1 2 3 4**

Visualization by Perturbation

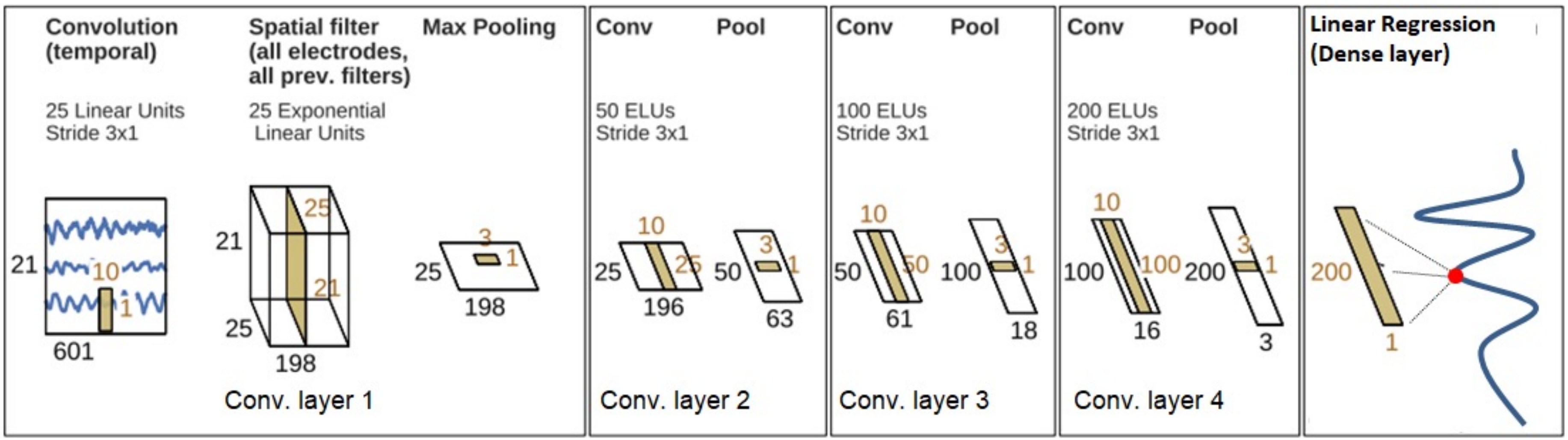


Perturbation Results



Hartmann et al. 2018

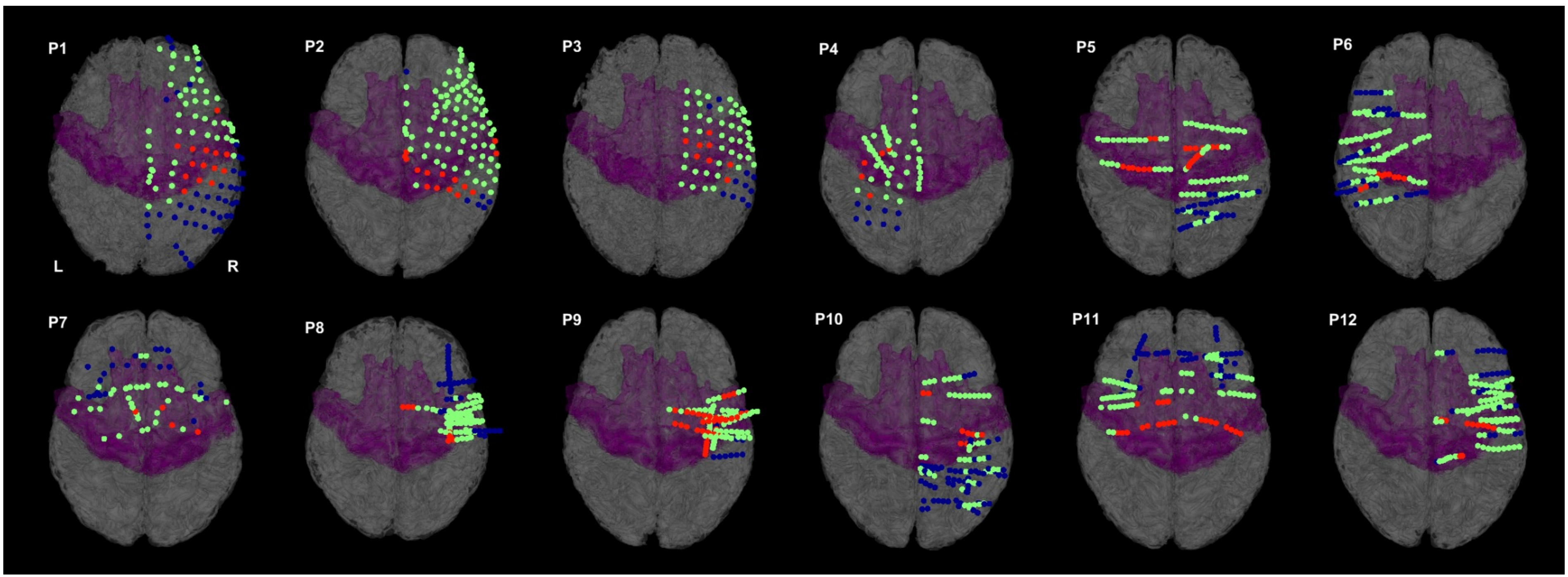
Deep4: CNN for EEG (regression problem)



Hammer et al. 2019 – in prep.

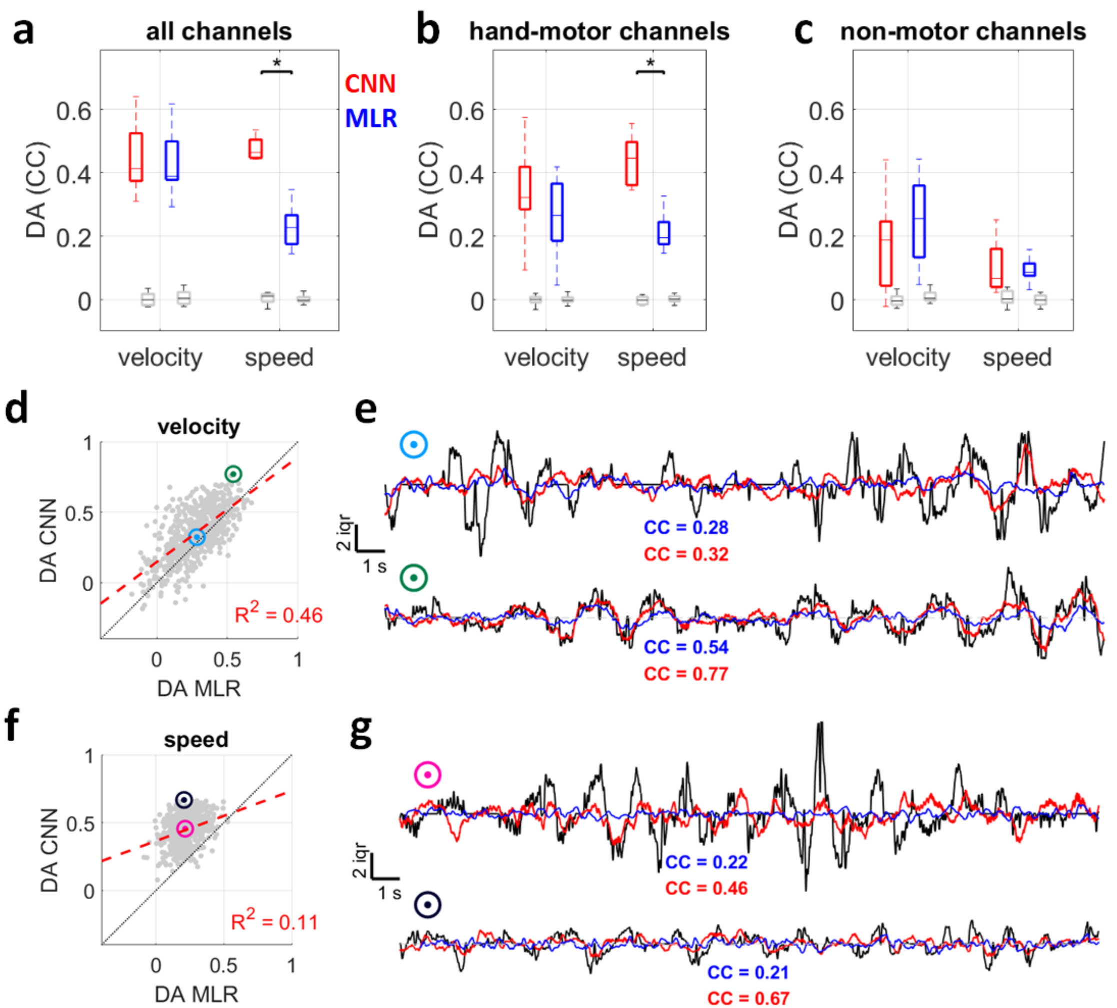
<u>Investigate learned filters of convolutional layers: **1 2 3 4**</u>

12 epilepsy patients with intracranial EEG implantations in motor cortex



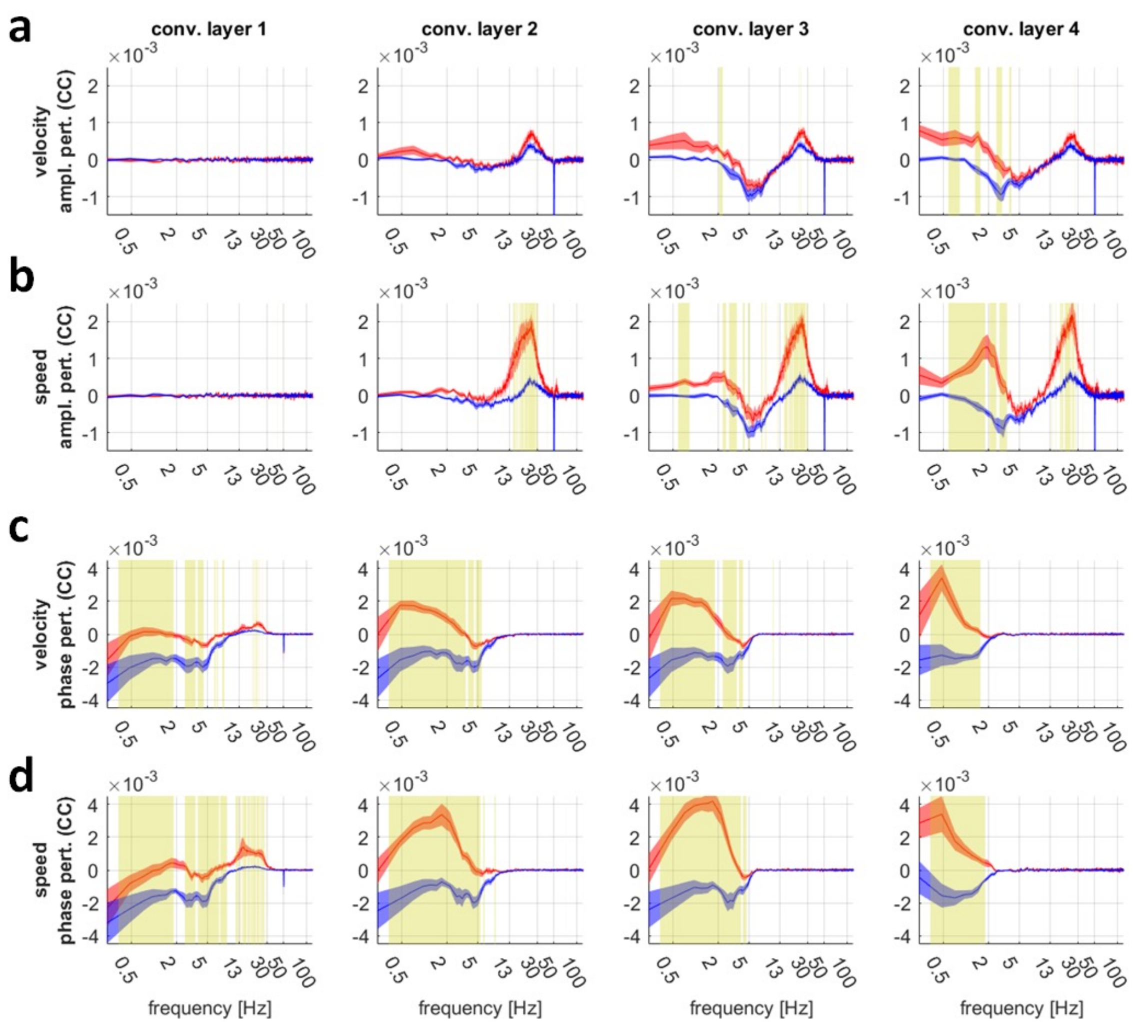
Hammer et al. 2019 – in prep.

Convolutional neural networks outperform multiple linear regression



Hammer et al. 2019 – in prep.

Network sensitivity to amplitude and phase perturbations



Hammer et al. 2019 – in prep.

Deep learning for iEEG decoding

- Convolutional neural networks (CNNs) are capable of *end-to-end* learning to decode movement from intracranial EEG.
- CNNs outperformed MLR and extracted information from motor cortex.
- CNNs learned low-frequency phase and beta-band amplitude information.
- Different CNN filters specialized for different features.

BMI usage

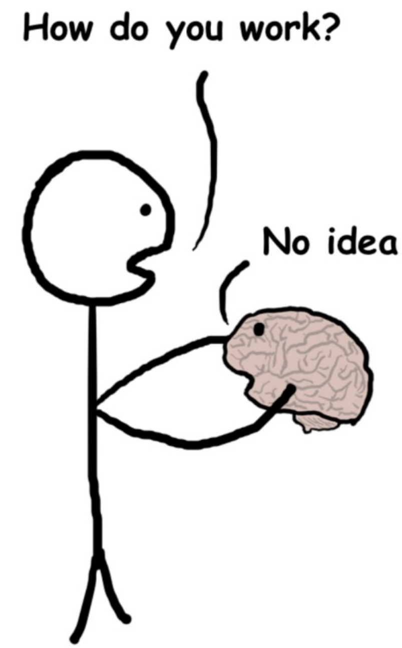
- Movement restoration
  - Paralyzed patients
- Neurorehabilitation
  - Patients after stroke
- Sensory restoration
  - Hearing: cochlear implants
  - Vision: retina / visual implants
- Brain stimulation
  - deep brain stimulation: Parkinson patients, depression, ...
  - epilepsy: seizure detection and stimulation
- Entertainment (gaming), ...

- Ethical issues!

Would you like to join our research?

- jirihammer@gmail.com

- Project, diploma thesis, PhD
  - ČVUT: doc. Daniel Novák, FEL
  - ČVUT: Dr. Radek Janča, katedra teorie obvodů, FEL
  - 2. LF UK: Prof. Petr Marusič



- Topics: closed-loop (with feedback) BCI
  - interdisciplinary (bioingeneering, medicine, machine learning, stat. data analysis, hardware communication, software implementation, ...)
  - using iEEG
  - cooperation with
    - University of Freiburg (DE): Prof. Ball
    - University of Grenoble (FR): Prof. Bastin

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- Uni Clinic, Freiburg
  - Tonio Ball
  - Tobias Pistohl
  - Joos Behncke
  - Martin Völker
  - Andreas Schultze-Bonhage
  - ...
- 2. LF UK a FN Motol
  - Petr Marusič
  - Adam Kalina
  - Pavel Čelakovský
  - Přemysl Jiruška
  - Pavel Kršek
  - ...

... a vám za pozornost

Bernstein Center Freiburg

UNIVERSITÄTS KLINIKUM FREIBURG

BrainLinks BrainTools
acting.thoughts
University of Freiburg

CAROLINAE FACULTAS MEDICA II UNIVERSITATIS MOTOL