Challenge I

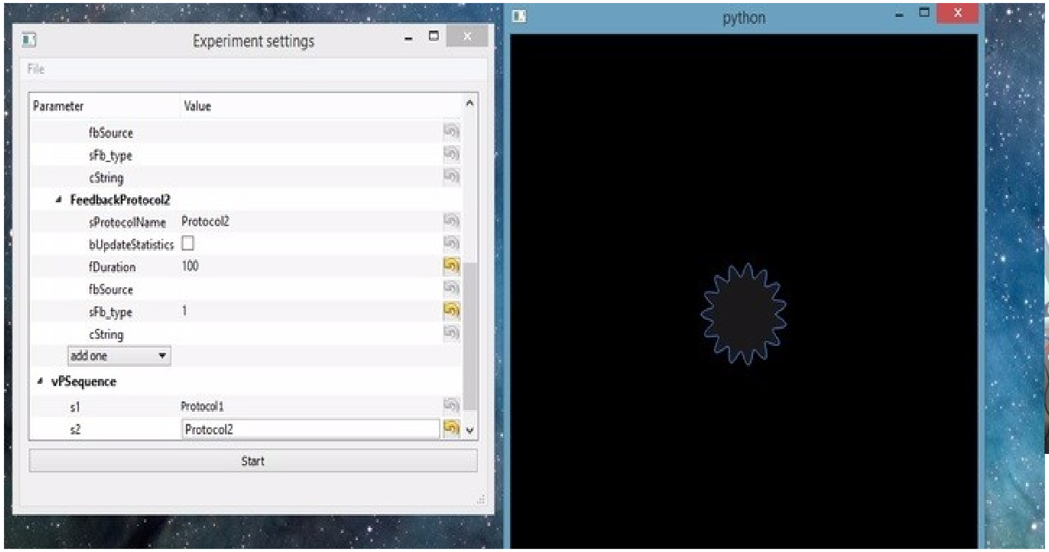
π-Neurofeedback

Predictive neurofeedback

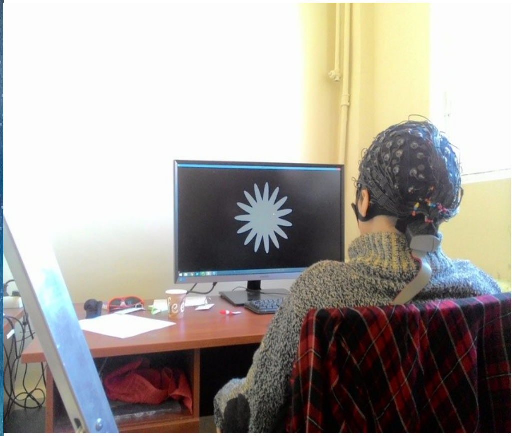
Neurofeedback paradigm implementation

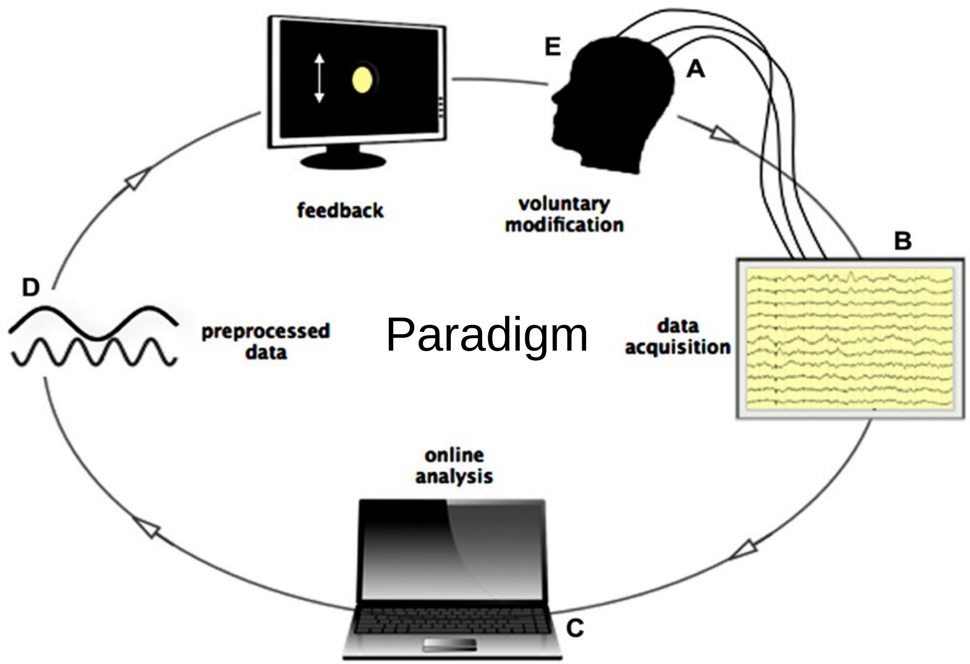
Hardware

Software

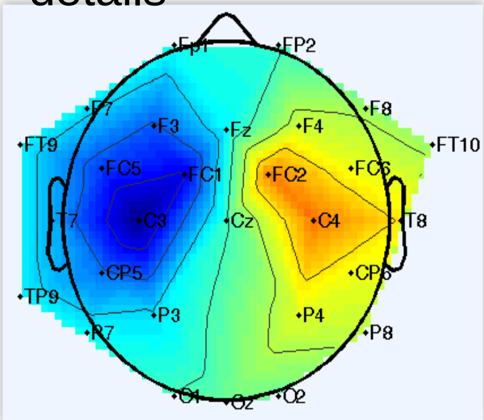


Setup





Unnecessary details



Different brain imaging modalities used in neurofeedback

- EEG
- MEG (Florin et al., 2013, Parkkonen, 2014)

- fMRI(Lawrence et al. 2014)

Kamiya, J. (1971). "Operant Control of the EEG Alpha Rhythm and Some of its Reported Effects on Consciousness". Biofeedback and Self-Control: an Aldine Reader on the Regulation of Bodily Processes and Consciousness.

1. Detect alpha-state after the beep

2. Enter high alpha state after promted by a beep

In 31 years ….

Consciousness and Cognition xxx (2012) xxx–xxx

Contents lists available at SciVerse ScienceDirect

Consciousness and Cognition

journal homepage: www.elsevier.com/locate/concog

ELSEVIER

Psychophysics of EEG alpha state discrimination

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A R T I C L E I N F O

Article history:
Received 11 January 2012
Available online xxxx

Keywords:
EEG
Alpha
Discrimination
Psychophysiology
Biofeedback
Neurofeedback
Psychophysics

A B S T R A C T

Nearly all research in neurofeedback since the 1960s has focused on training voluntary control over EEG constructs. By contrast, EEG state discrimination training focuses on awareness of subjective correlates of EEG states. This study presents the first successful replication of EEG alpha state discrimination first reported by Kamiya (1962). A 150-s baseline was recorded in 106 participants. During the task, low (<30th percentile of the baseline) and high alpha events (>70th percentile) triggered a prompt. Participants indicated "high" or "low" with a keypress response and received immediate feedback. Seventy-five percent of participants achieved significant discrimination within nine sessions, with a significant learning curve effect. Performance was significantly related to physical properties of the EEG signal, including magnitude, duration, and absolute vs. relative amplitude. These results are consistent with a conceptualization of EEG state discrimination as a sensory modality, although it is also intricately related to voluntary control of these states.

Different brain imaging modalities used in neurofeedback

- EEG
- MEG (Florin et al., 2013, Parkkonnen, 2014)
- fMRI(Lawrence et al. 2014)
- Joint fMRI-EEG (Zotev et al. 2014)

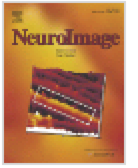
Applications of neurofeedback

- ADHD therapy*(Lofthouse et al. 2012), Depression*(Linden et al. 2012), epilepsy* (Sterman and Friar, 1972, Tan et al. 2009)*
- Boosting cognitive function (Bazanova et al, Zoefel B, 2011)
- Meditation, virtual guru, relaxation
- To improve performance of BCI users

Renaissance of neurofeedback

NeuroImage

Volume 49, Issue 1, 1 January 2010, Pages 1066–1072



Neurofeedback: A promising tool for the self-regulation of emotion networks

S.J. Johnston[a], S.G. Boehm[a], I

[a] Bangor Imaging Unit, Wolfson Centre
Bangor, UK

[b] Department of Psychological Medicin

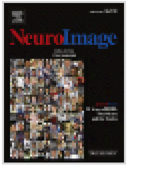
[c] North West Wales NHS Trust, Bango

[d] Department of Cognitive Neuroscien
Netherlands

NeuroImage

Volume 62, Issue 2, 15 August 2012, Pages 682–692

20 YEARS OF fMRI — 20 YEARS OF fMRI



Review

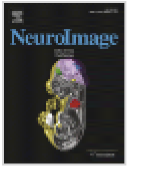
Real-time fMRI and its application to neurofeedback

Nikolaus Weiskopf

Wellcome Trust Centre for Neuroimagin
WC1N 3BG, UK

NeuroImage

Volume 54, Issue 2, 15 January 2011, Pages 1427–1431



IF ~ 6-7

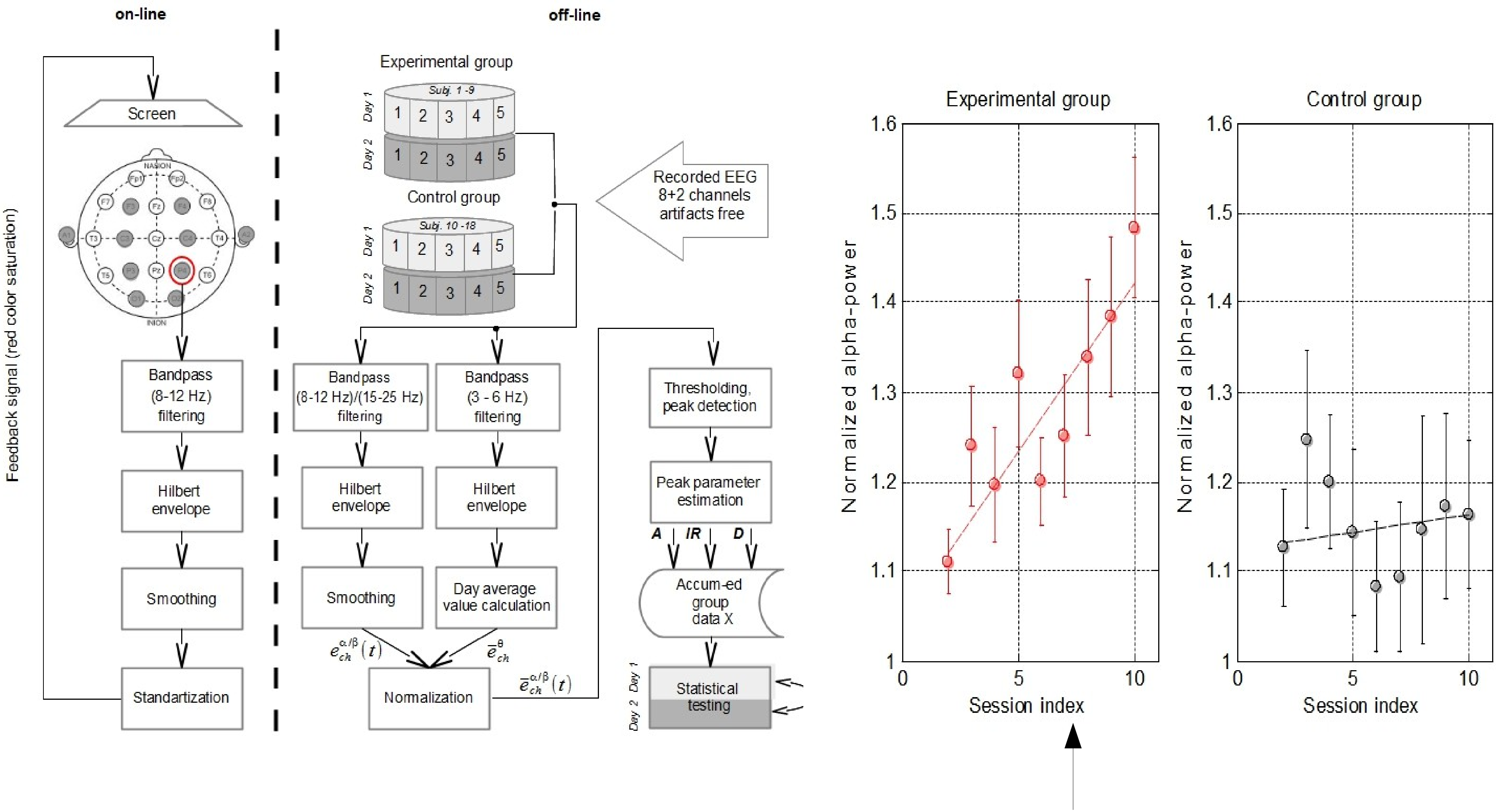
Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance

Benedikt Zoefel[a], René J. Huster[b], Christoph S. Herrmann[b]

[a] Otto-Von-Guericke-University, Institute for Biology, Madeburg, Germany

[b] Carl-Von-Ossietzky University Oldenburg, Department of Psychology, Experimental Psychology Lab, Oldenburg, Germany

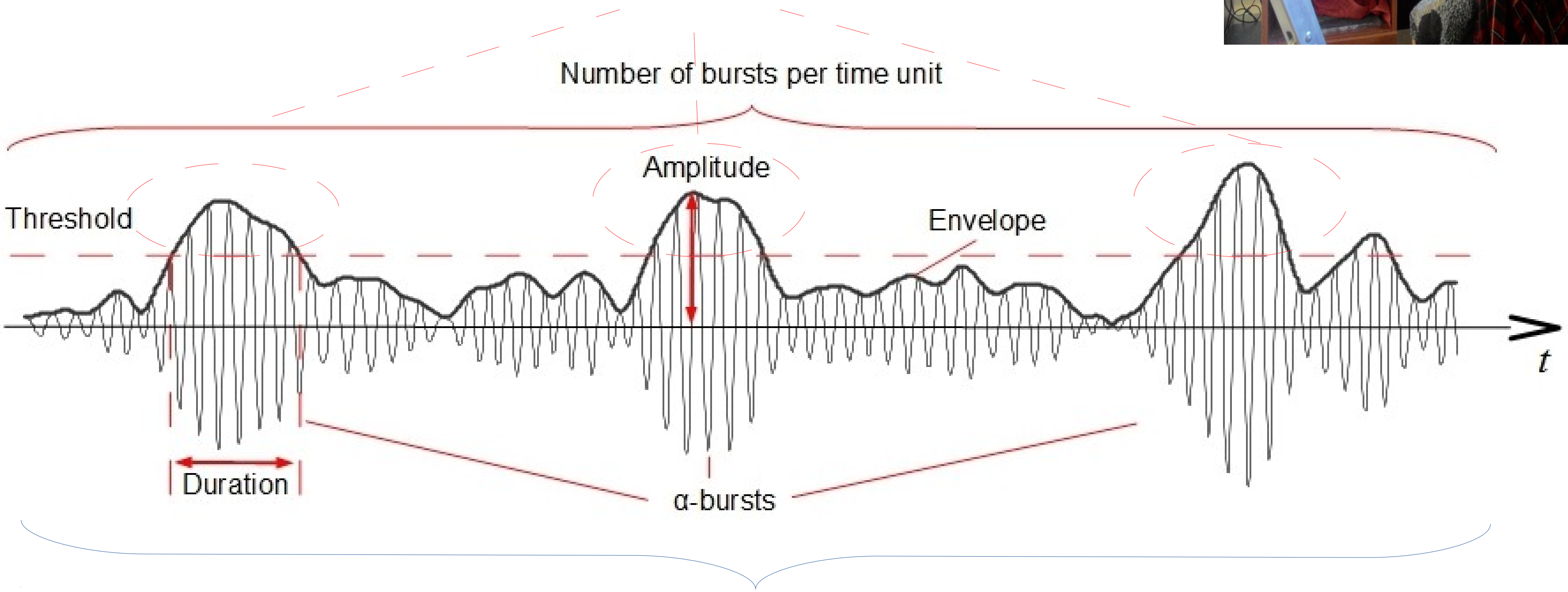
Our experiment



How does the brain do this ?

Force the brain to change its activity pattern

Desired (target states)

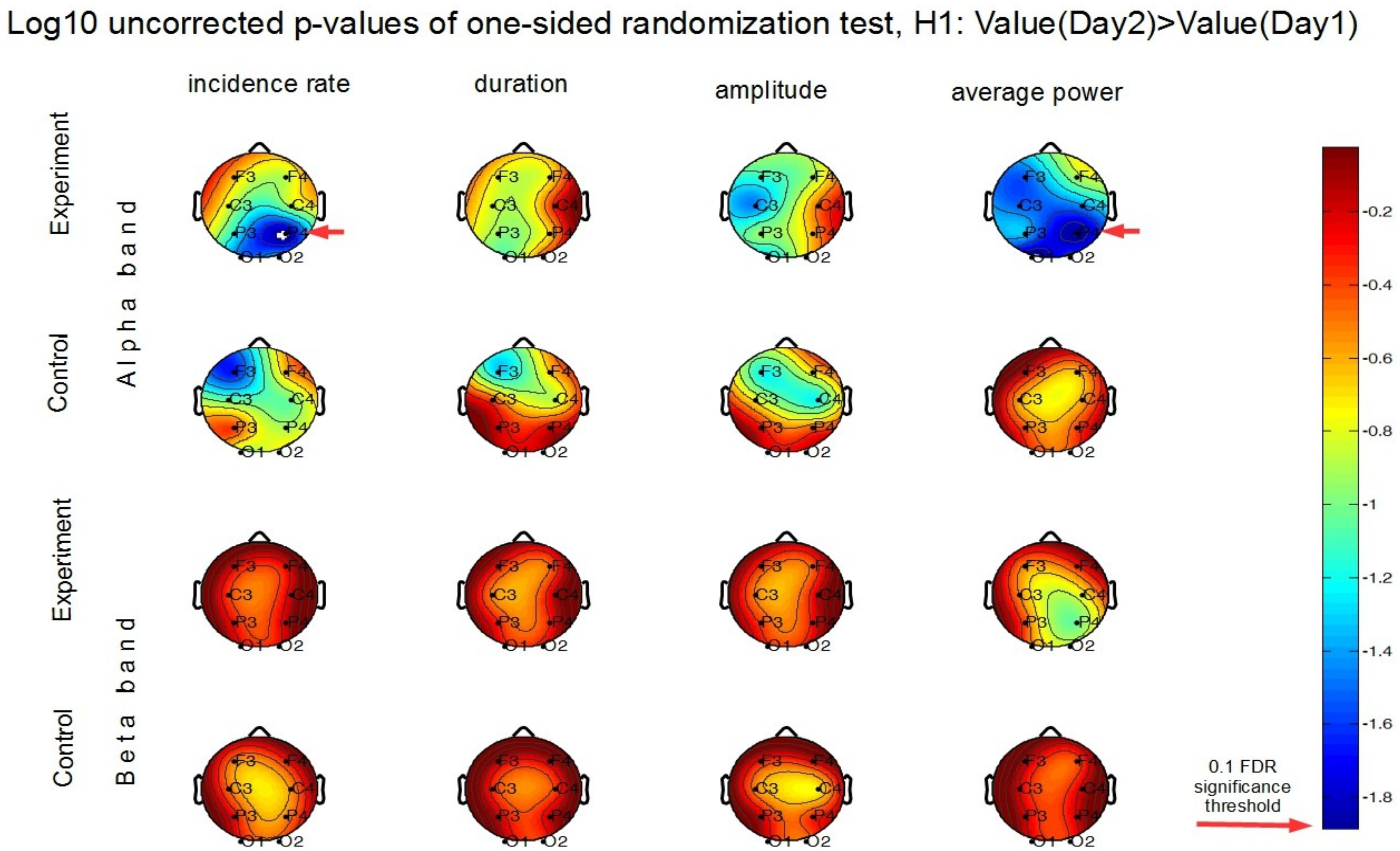


The goal of training is to maximize
the average power of alpha-rythm.

1. Increase amplitude of each burst?
2. Increase incidence rate of the bursts?
3. Increase burst duration?

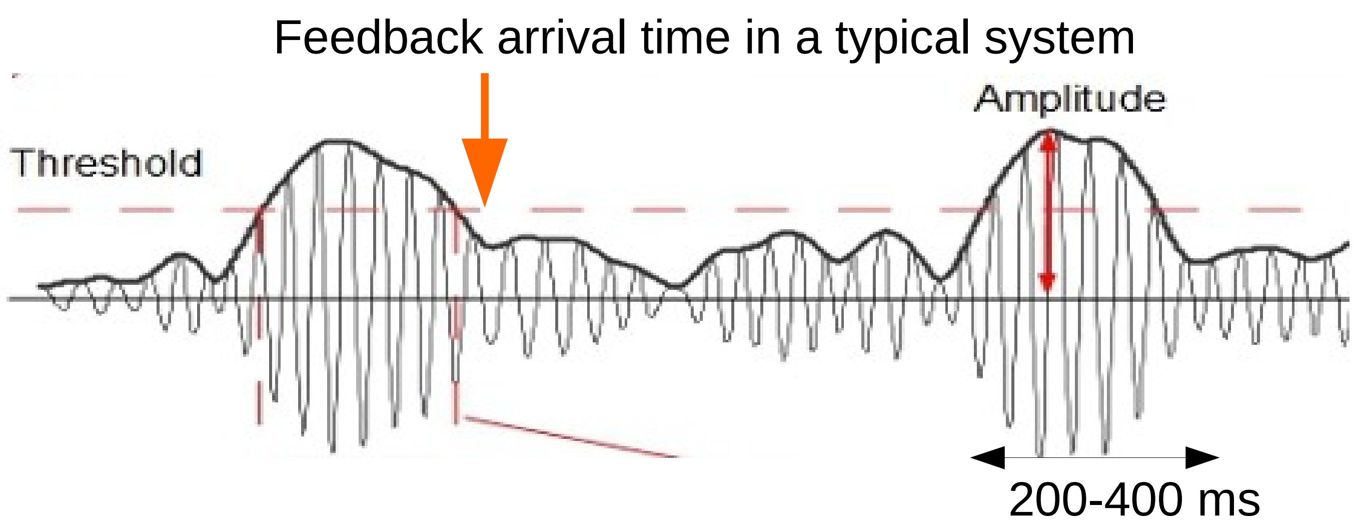
Which?

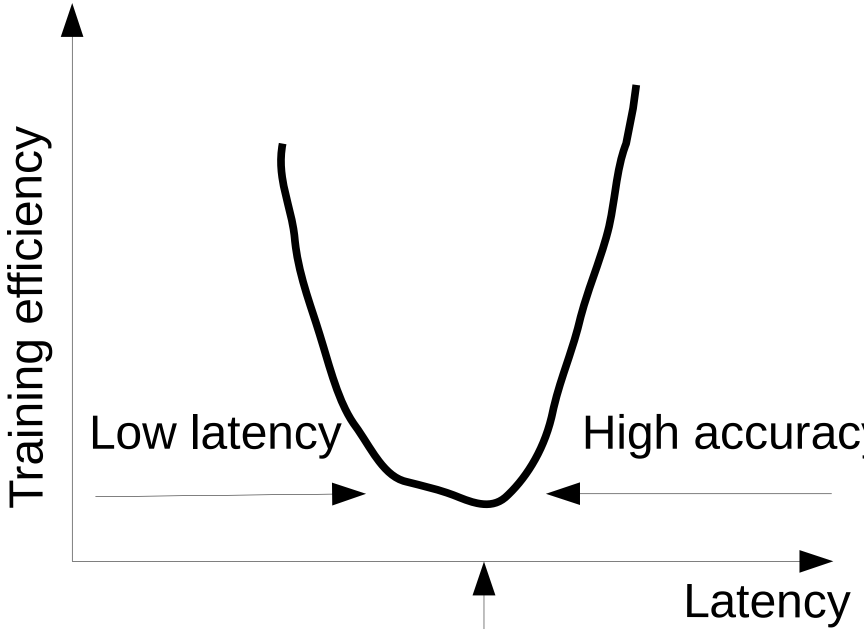
The brain learns to more easily ***enter the target state*** and not to change its properties (amplitude and duration)!!



Ossadtchi et al. 2016, SciRep – under review

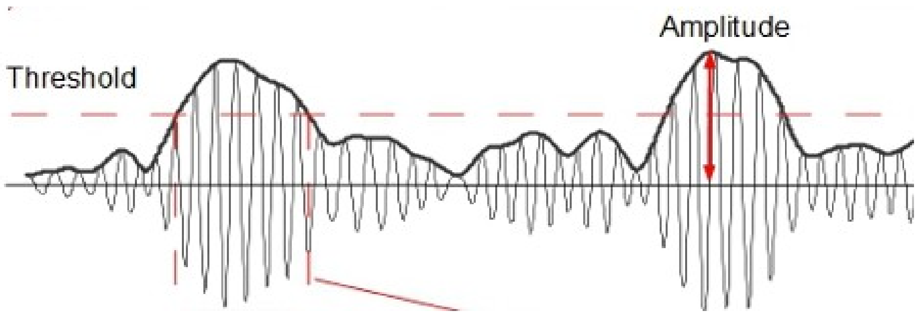
Trade off between the accuracy and latency

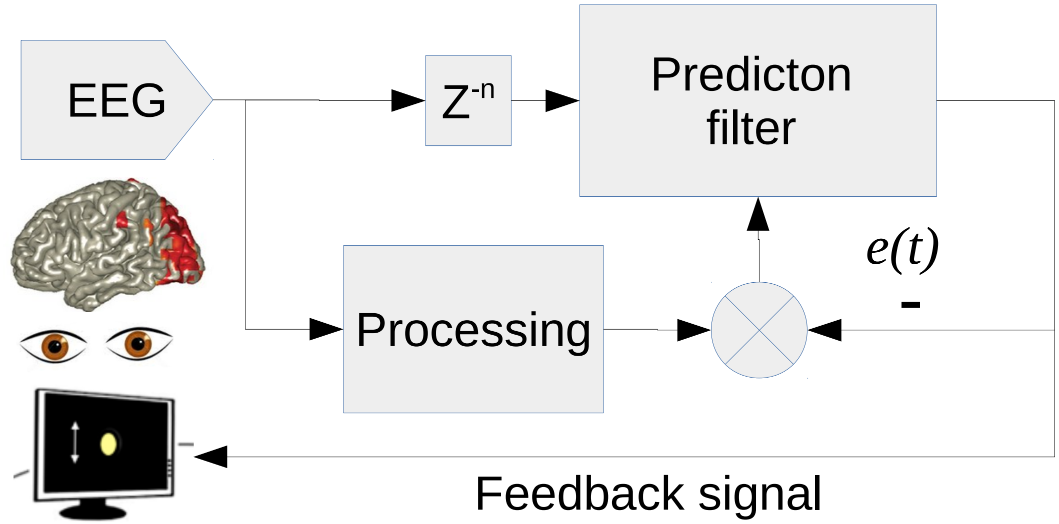


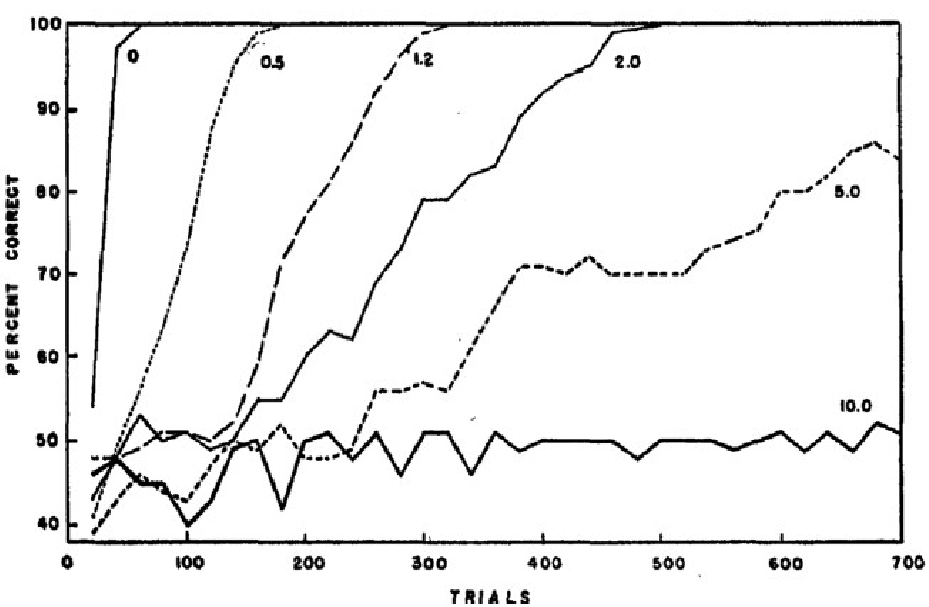


Reinforcement signal latency reduction

Estimation of band power requires time (fundamentally)



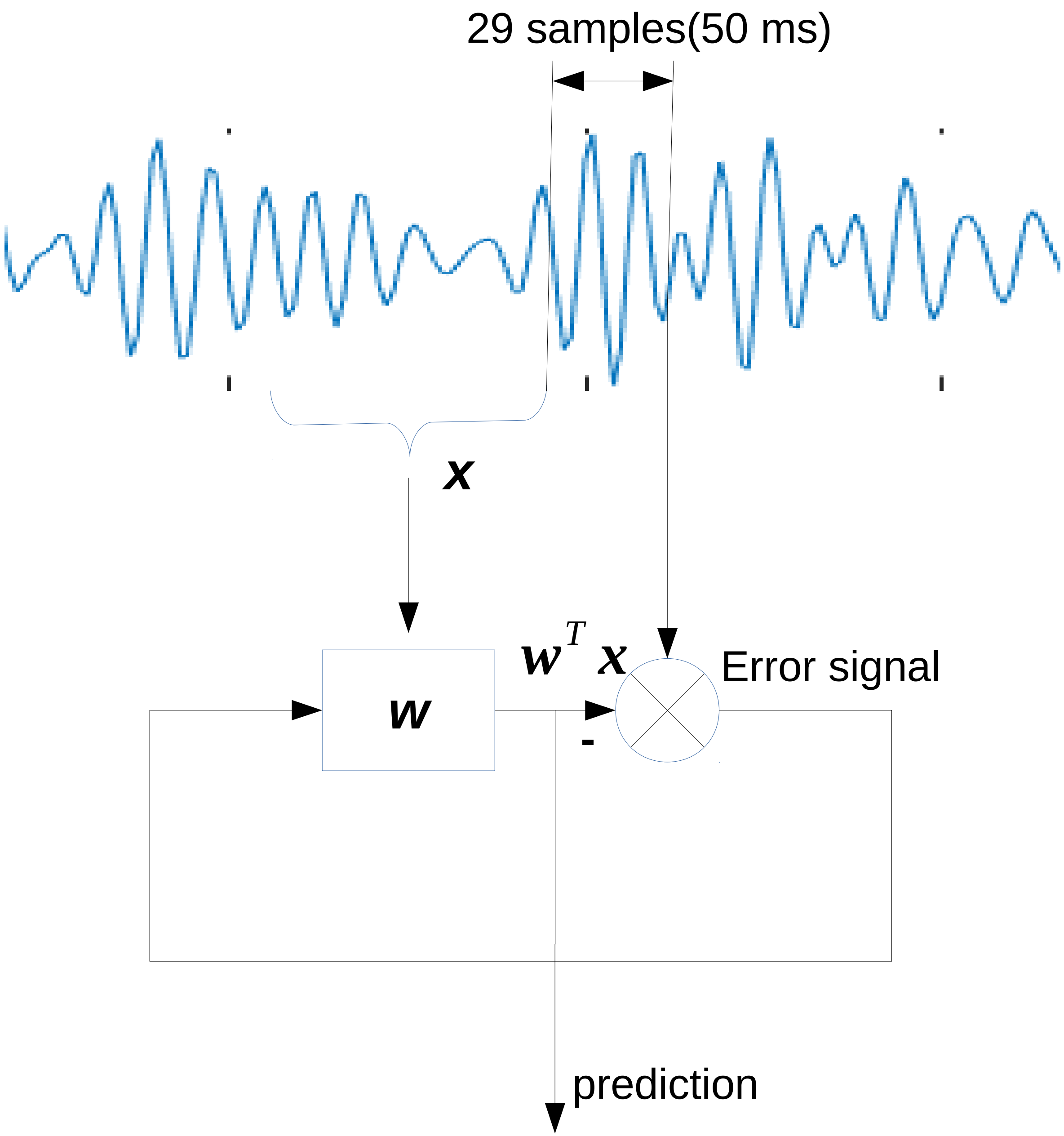




- Estimation of the target functional introduces the delay and therefore the reward signal looses temporal specificity which leads to the reduced learning efficiency

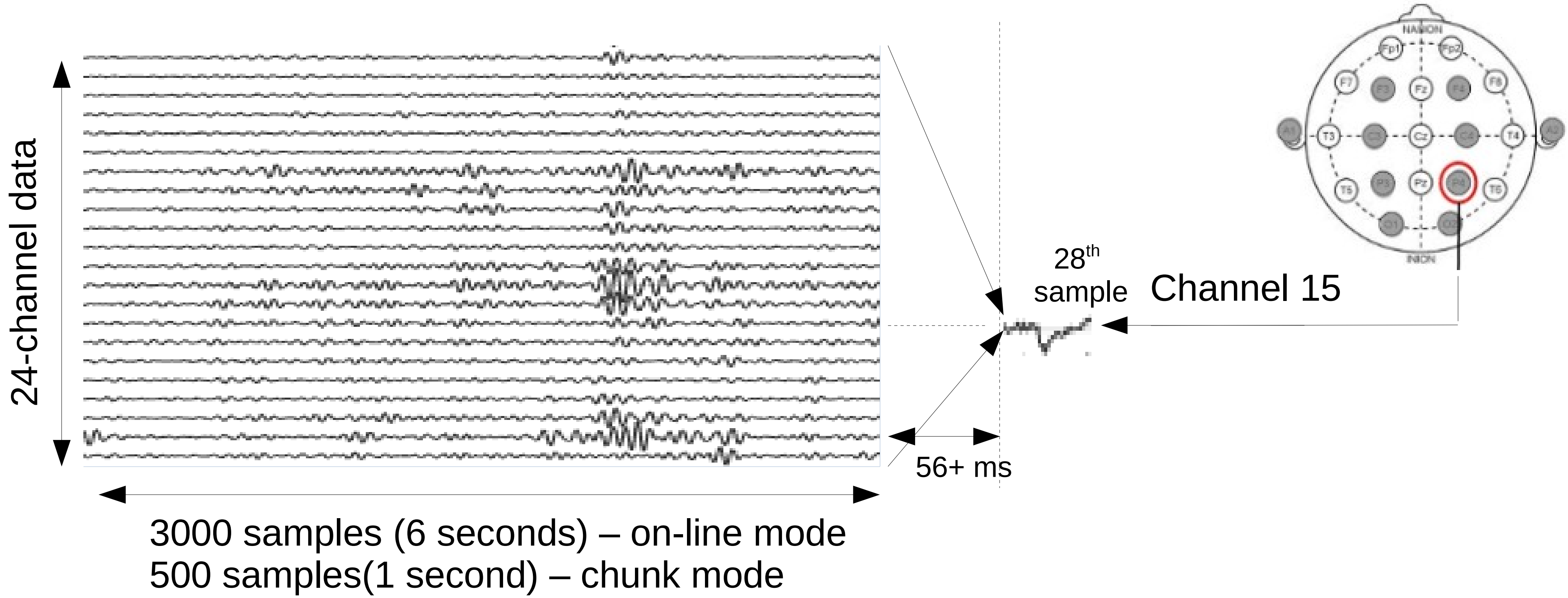
- Adaptive signal processing techniques allow to predict the EEG signal forward and compensate for the mentioned delay and thus increase the efficiency of neurofeedback therapy.

Baseline solution and your task



- Use Recursive Least Squares algorithm to adapt the linear filter weights
- 3 taps into the past, all channels
- Use all the channels data and form ***x*** by stacking the lagged samples into a single vector
- Use only the error from the far (29 samples) future to adapt the coefficients
- Try to predict 29-36 samples in the future!

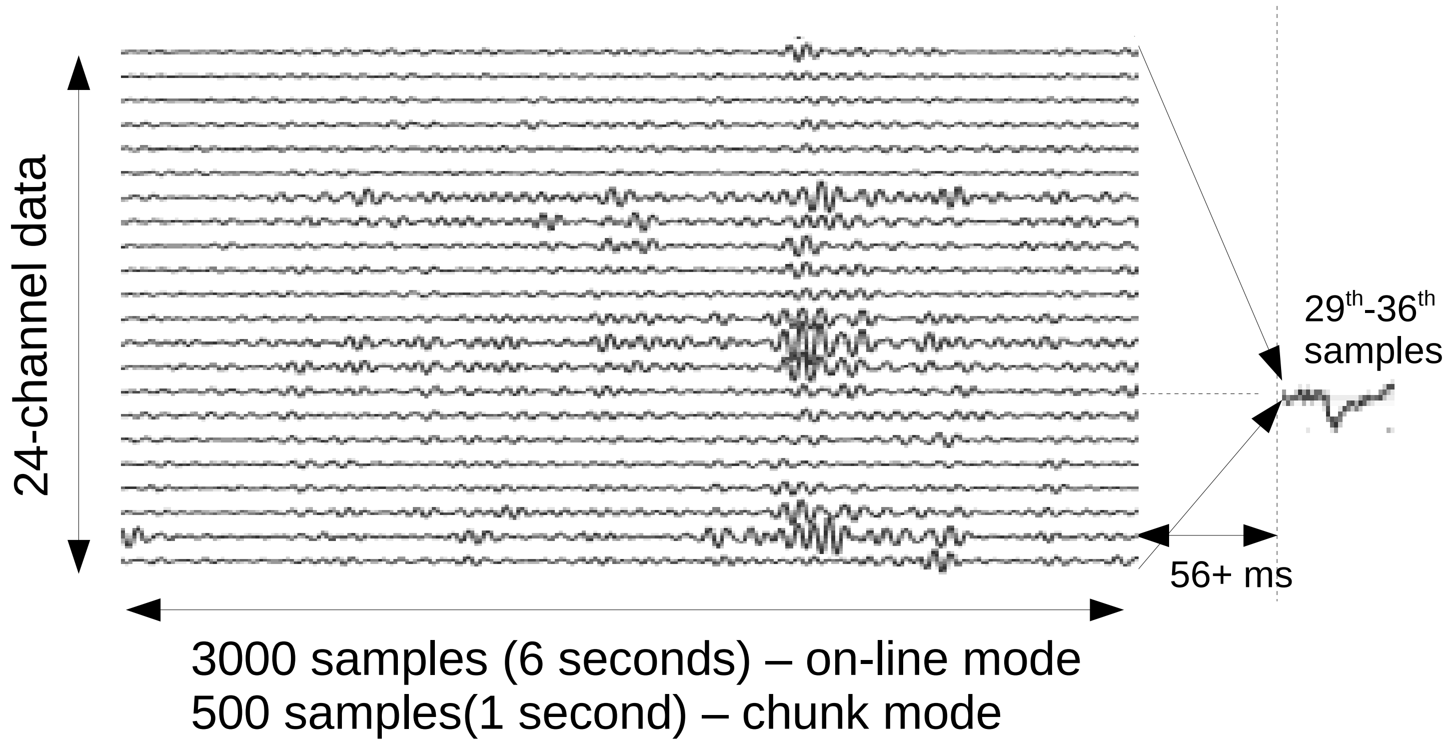
Testing your algorithm



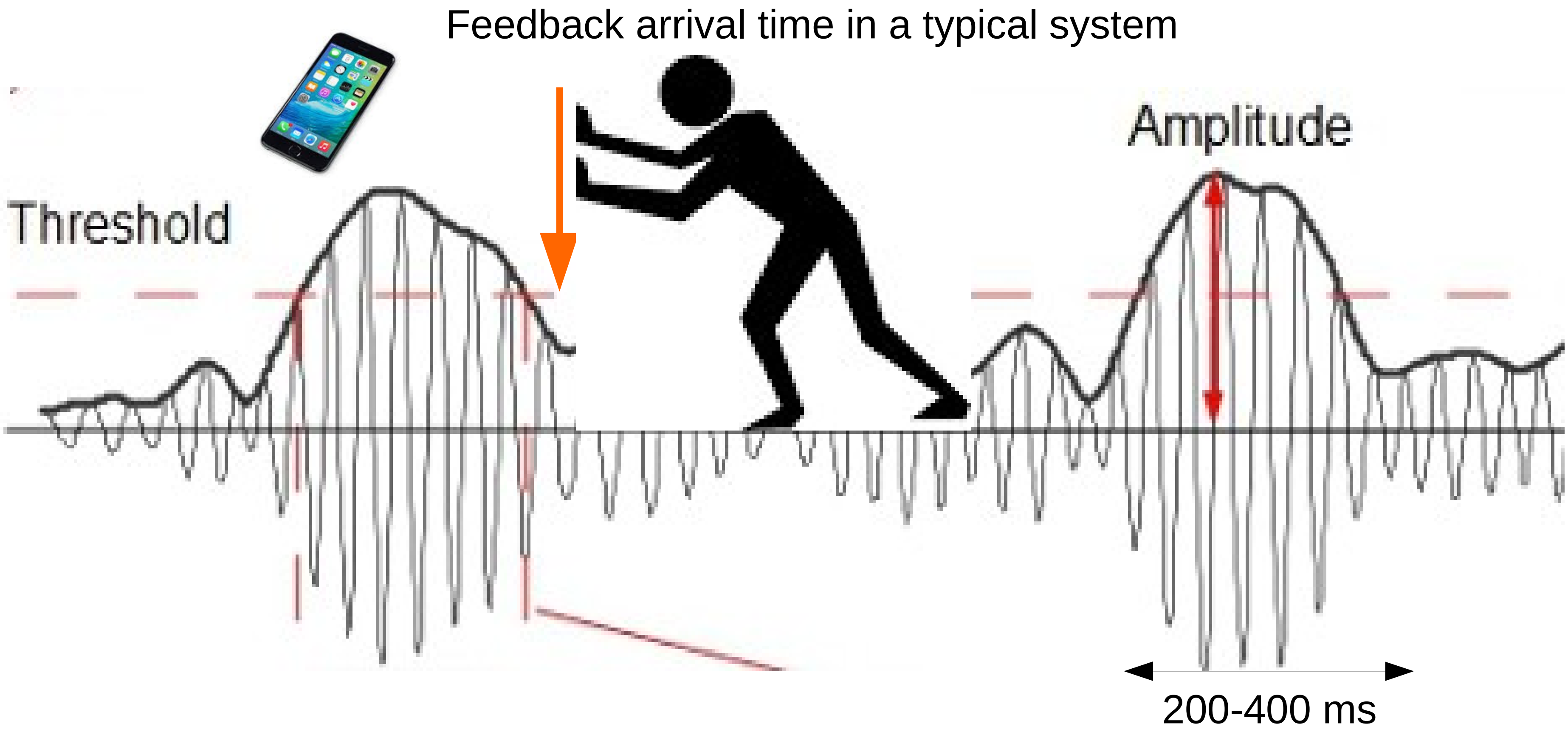
- 8-12 Hz filtered EEG from 24 channels
- The goal is to predict forward for 56 ms data in channel 15 (P4)
- You can use all the channels to calculate prediction
- The predictor can be adaptive and its params can be re-estimated as we go BUT, you have to understand that this re-estimation is done based on the error signal which(in the real-time prediction mode) you will get only in 56 ms(28 samples)!

Performance metrics

- E = Mean squared error averaged over for the 29th-36th sample after the end of each chunk
- Q = 10000(2-E)



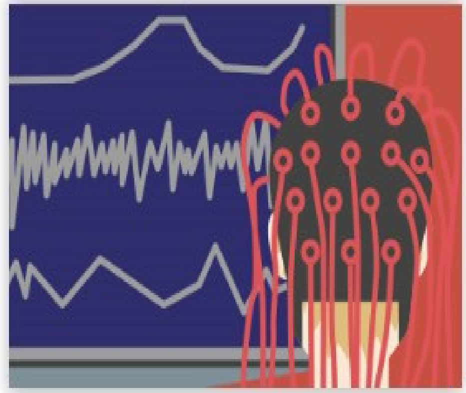
Push it back!
π-Neurofeedback!



Challenge II

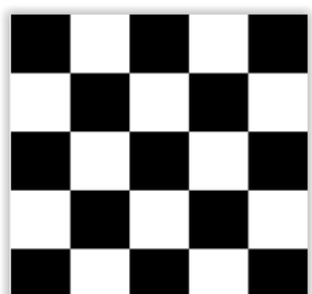
Command decoding in an asynchronous motor-imagery BCI

Non-invasive brain-computer interface systems

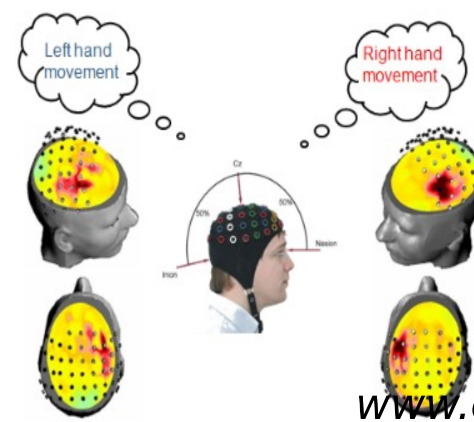


Positional

SSVEP



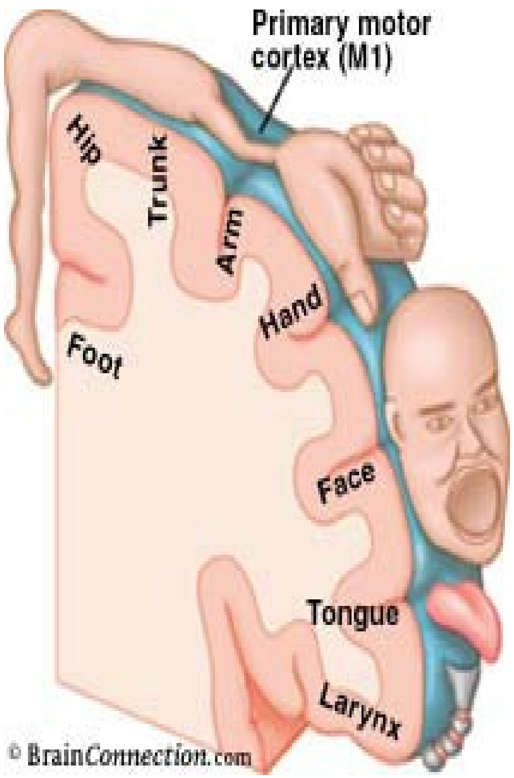
Imaginary movements

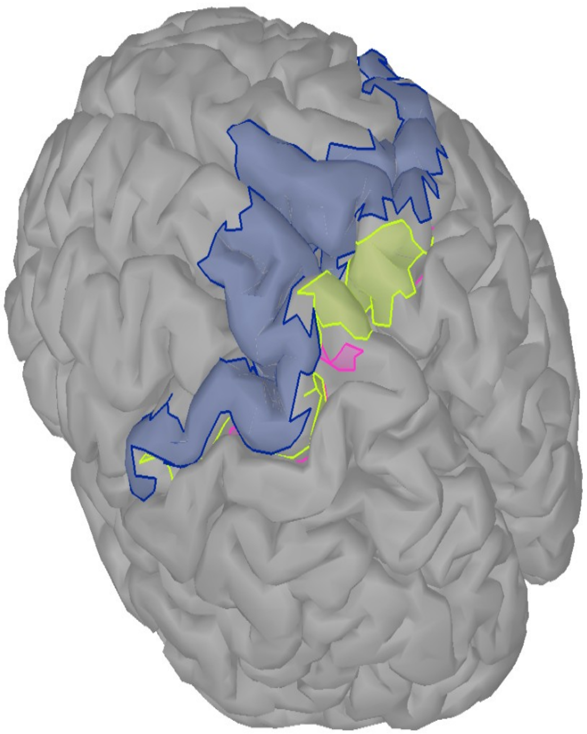


С. Шишкин, Коммерсантъ НАУКА, 4 (2015)

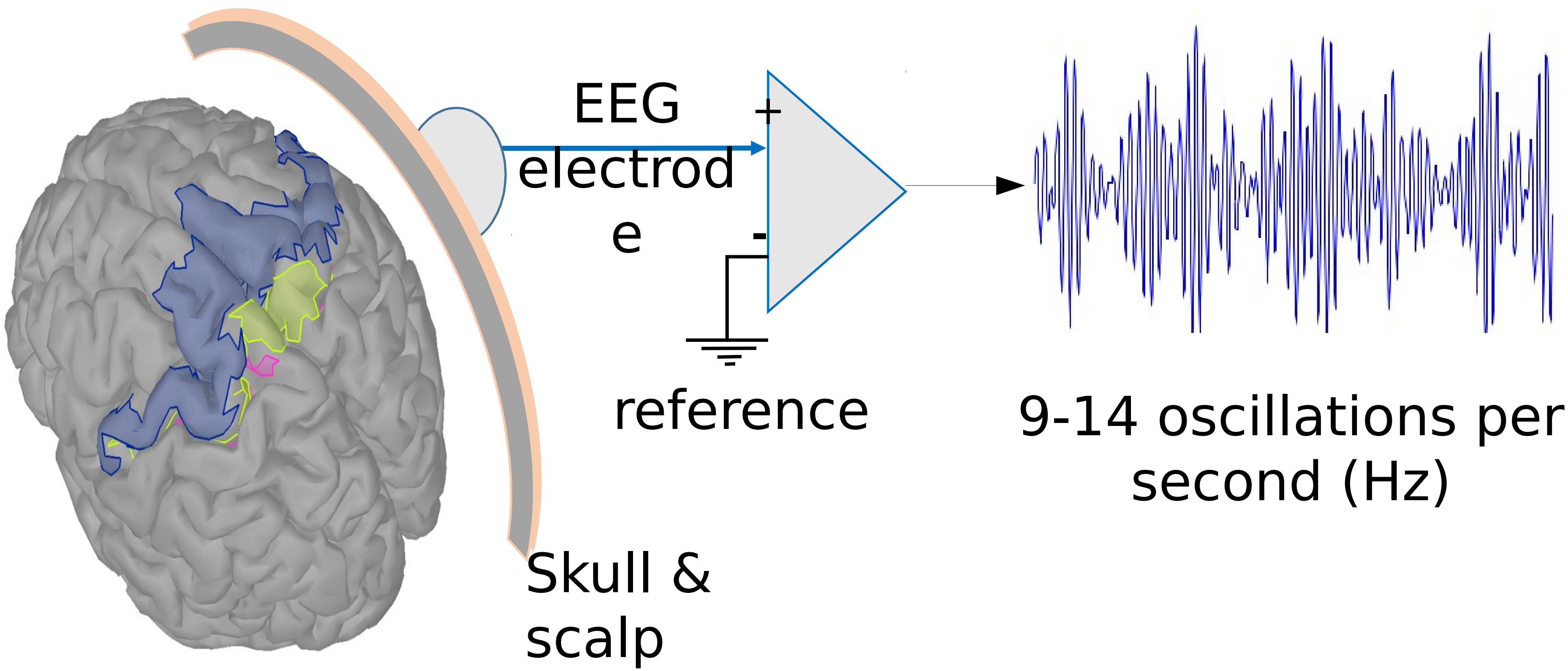
www.gtec.at

Сенсомоторная кора и зоны представительства

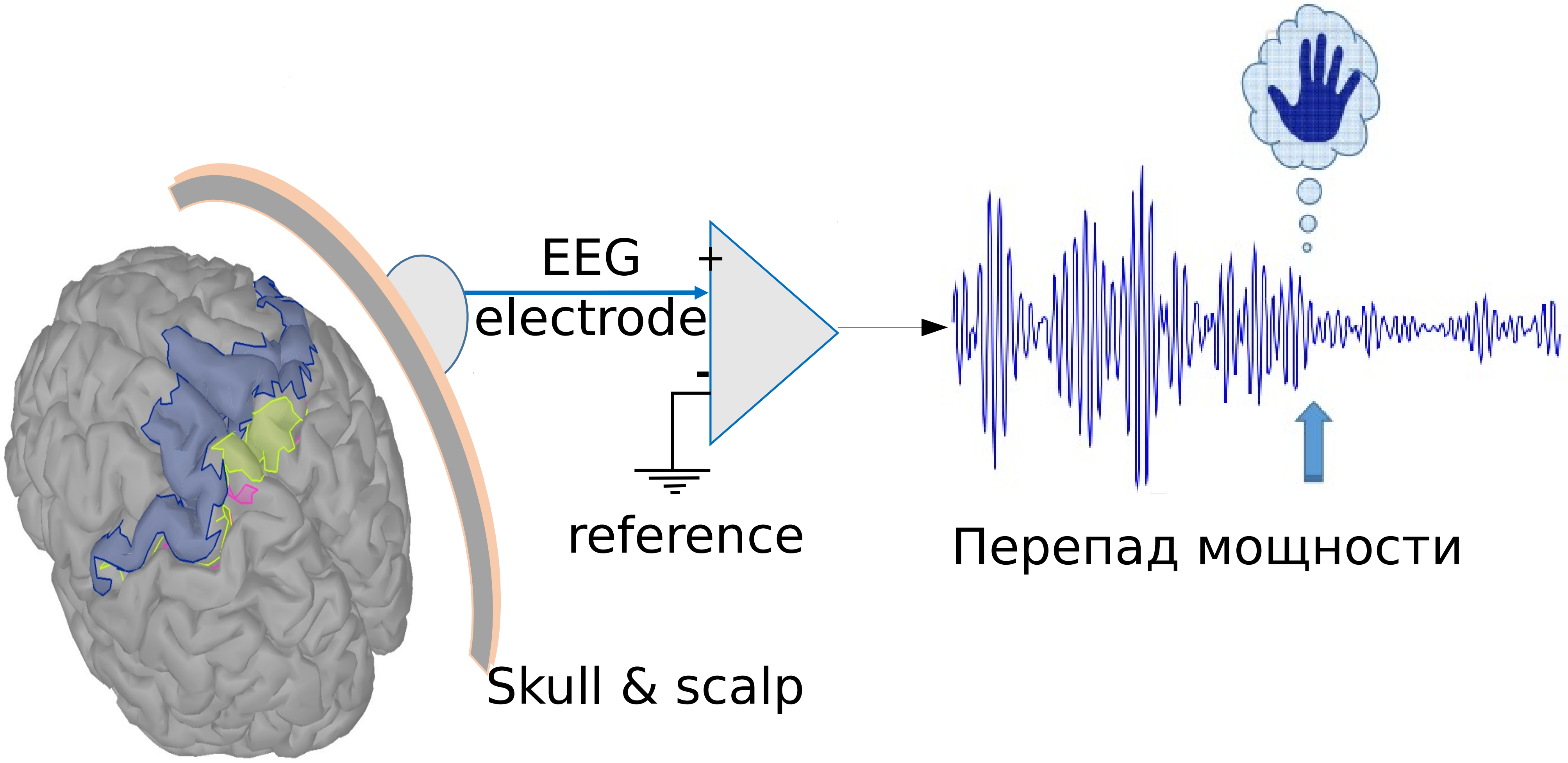




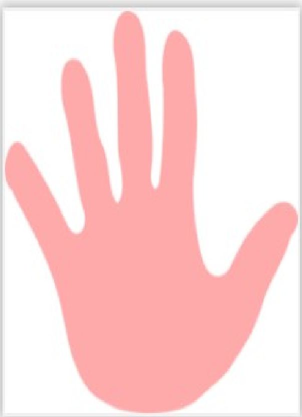
Sensory-motor rhythm

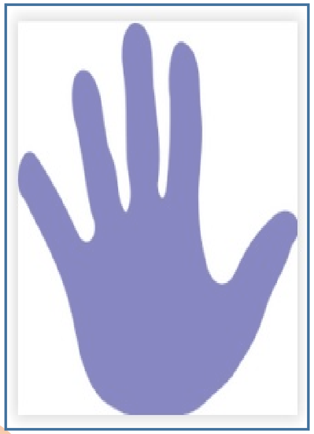


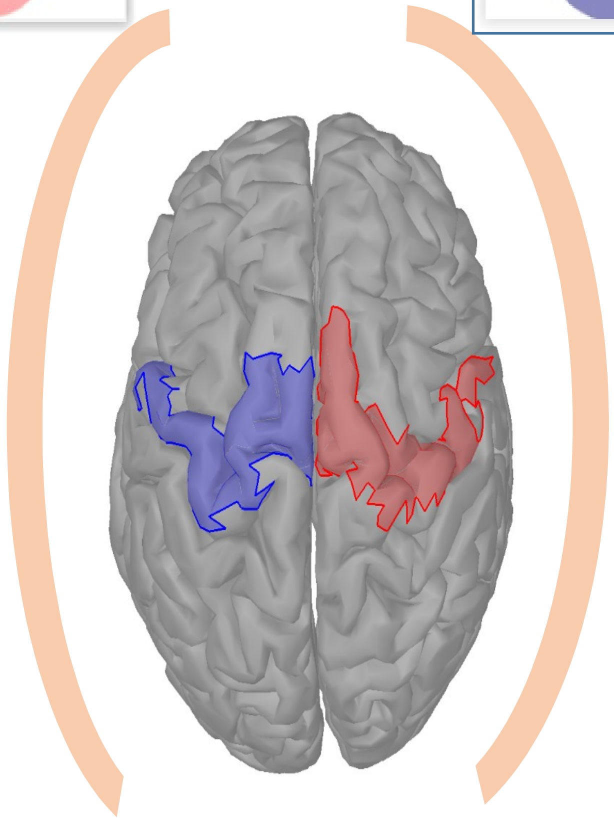
SMR desynchronization

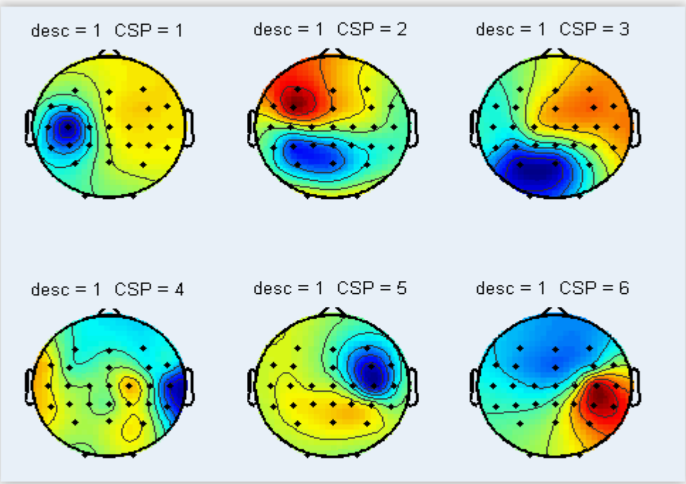


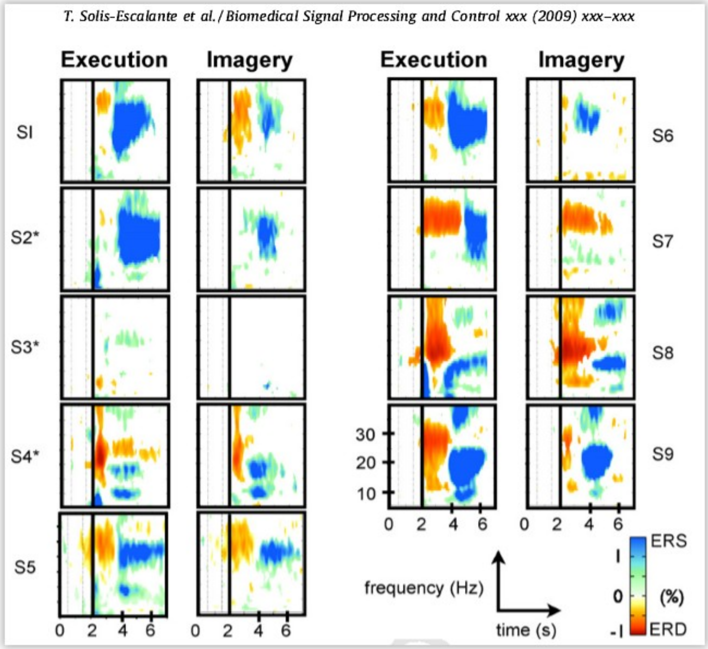
Lateralization & frequency specificity



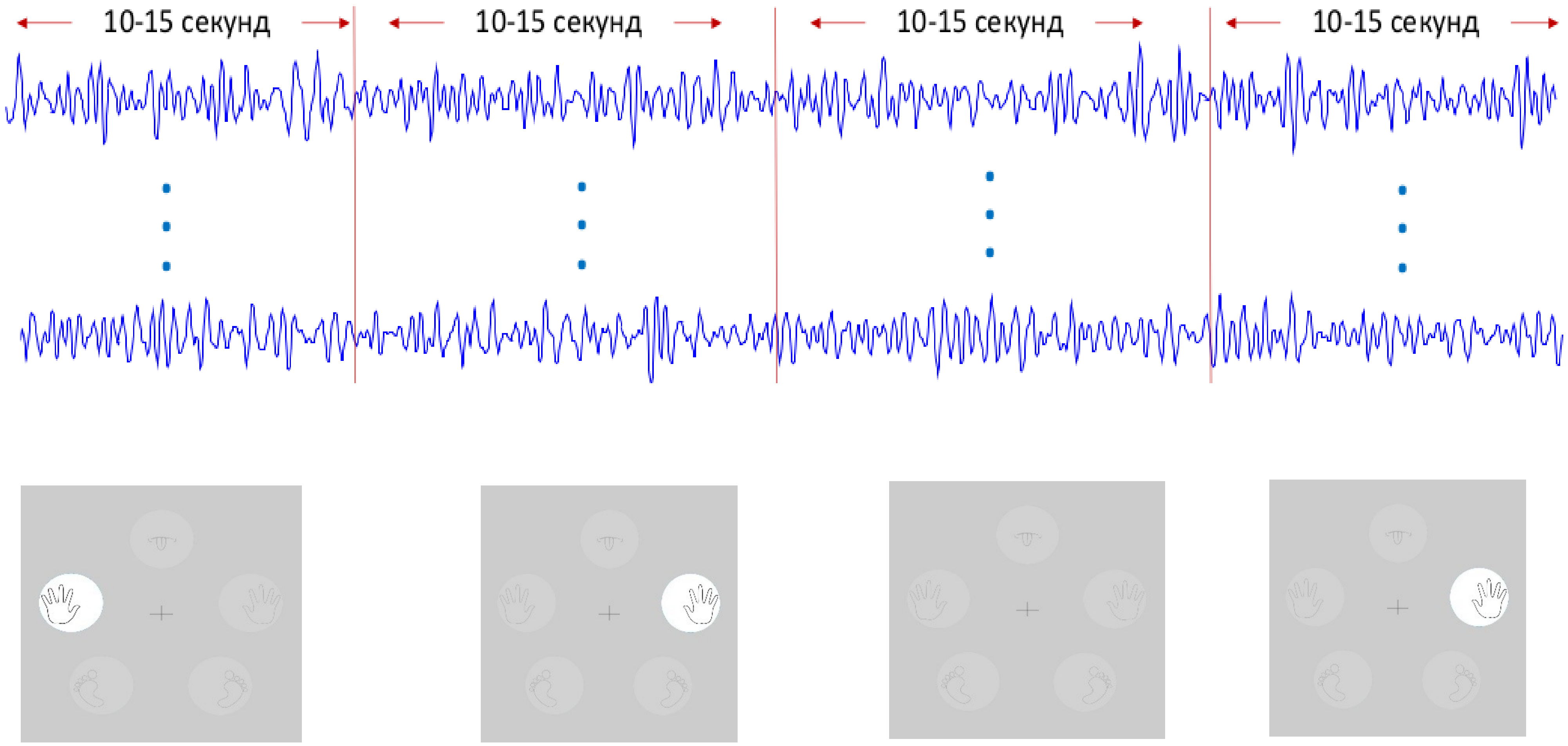




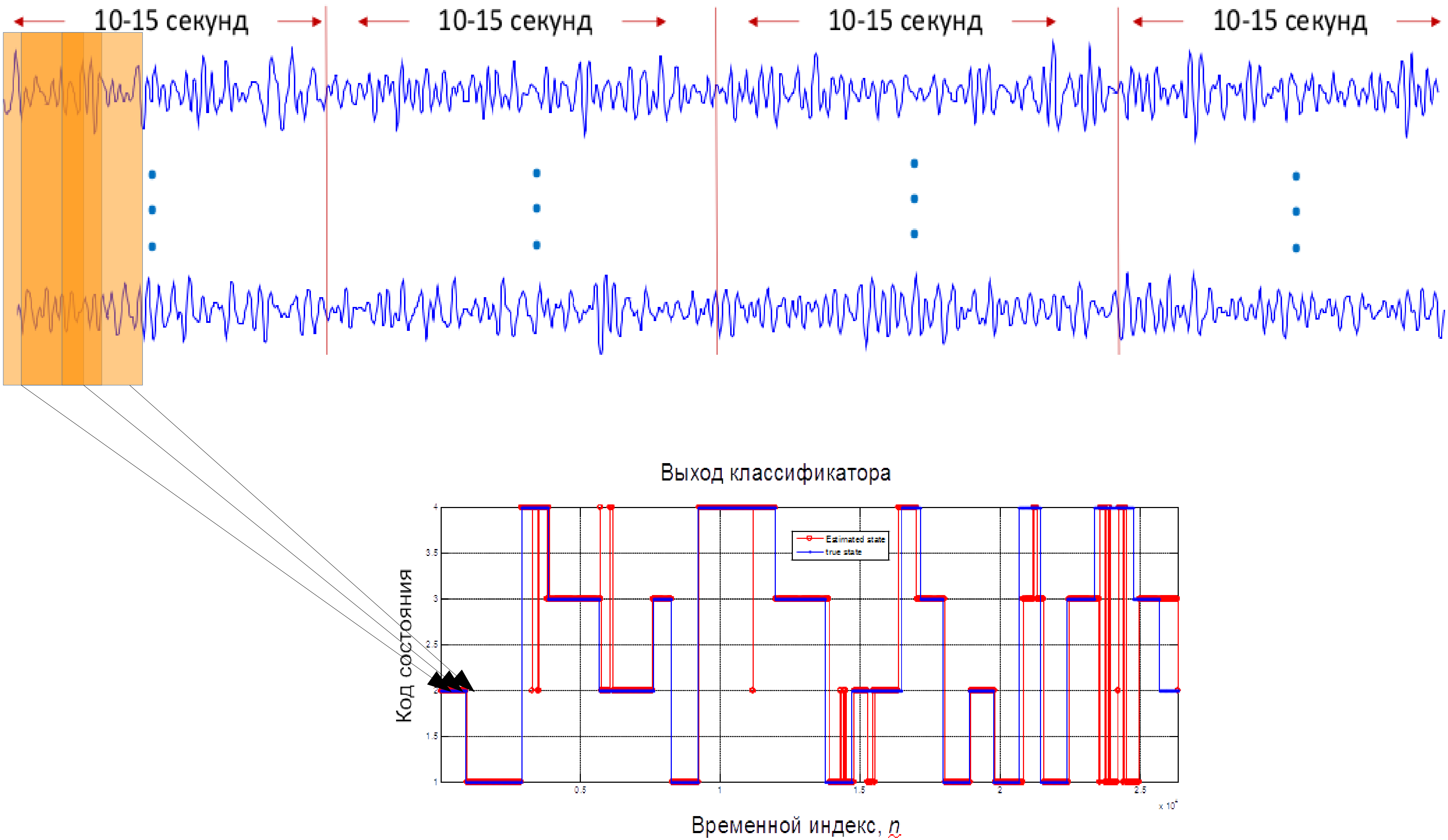




Training mode



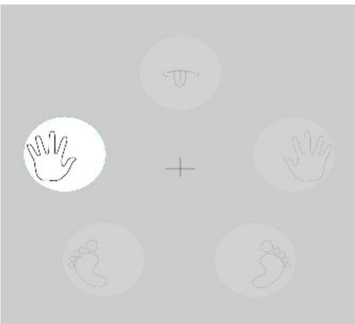
Testing the system



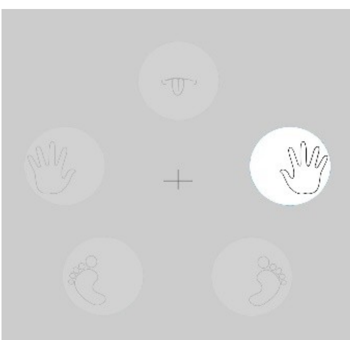
Common Spatial Patterns Analysis

X(t), Data condition 1

N channels



C_1

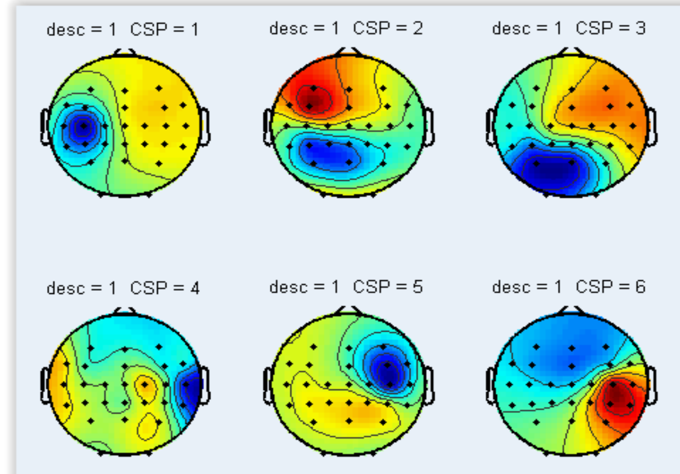


N channels

X(t), Data condition 2

C_2

$$\frac{w^T C_1 w}{w^T C_2 w} \rightarrow \max$$



$$G = C_X W C_q^{-1}$$

Use generalized eigenvalue decomposition to find w

$$z_i(t) = \boldsymbol{w}_i^T \boldsymbol{X}(t)$$

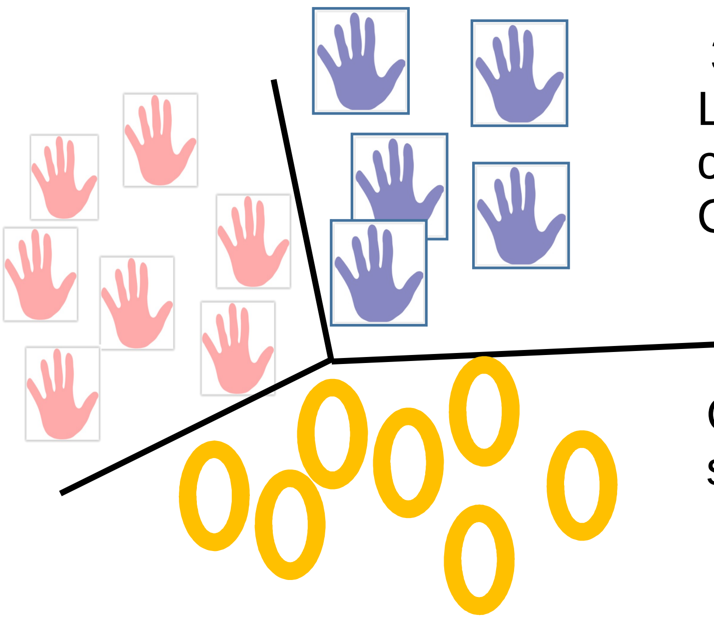
Compute component timeseries by projecting the multichannel data onto ***w***

Haufe et al, 2014, Neuroimage

Data and Task

- 3 classes (left hand, right hand, rest)
- For training you get **continuous** multichannel EEG recordings with labels
- For testing you get 4-second **chunks** of multichannel EEG data with class labels
- Build a classifier that converts the 4-second chunks into commands
- Test data are split into private and public halves
- The best algorithms will be included in the BCI system on Sunday and you will have a chance to play with it!
- 10000*mean(ROC AUC[1 vs all])

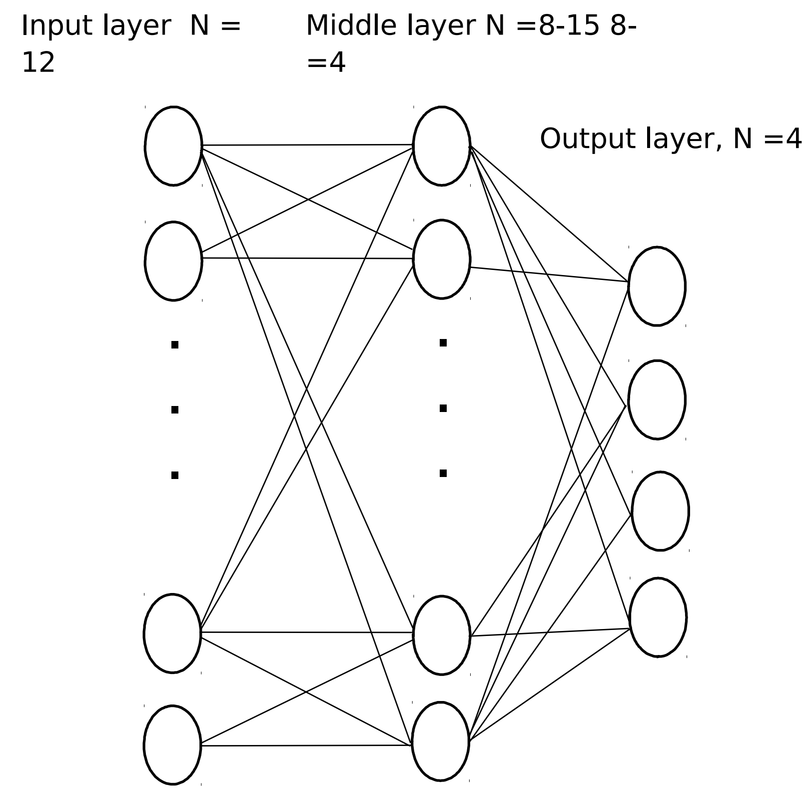
Baseline Solution



3 CSP one versus all
Lasso regression for
components selection
Component timeseries

$$z_i(t) = \boldsymbol{w}_i^T \boldsymbol{X}(t)$$

Component power in a
sliding 500 ms window



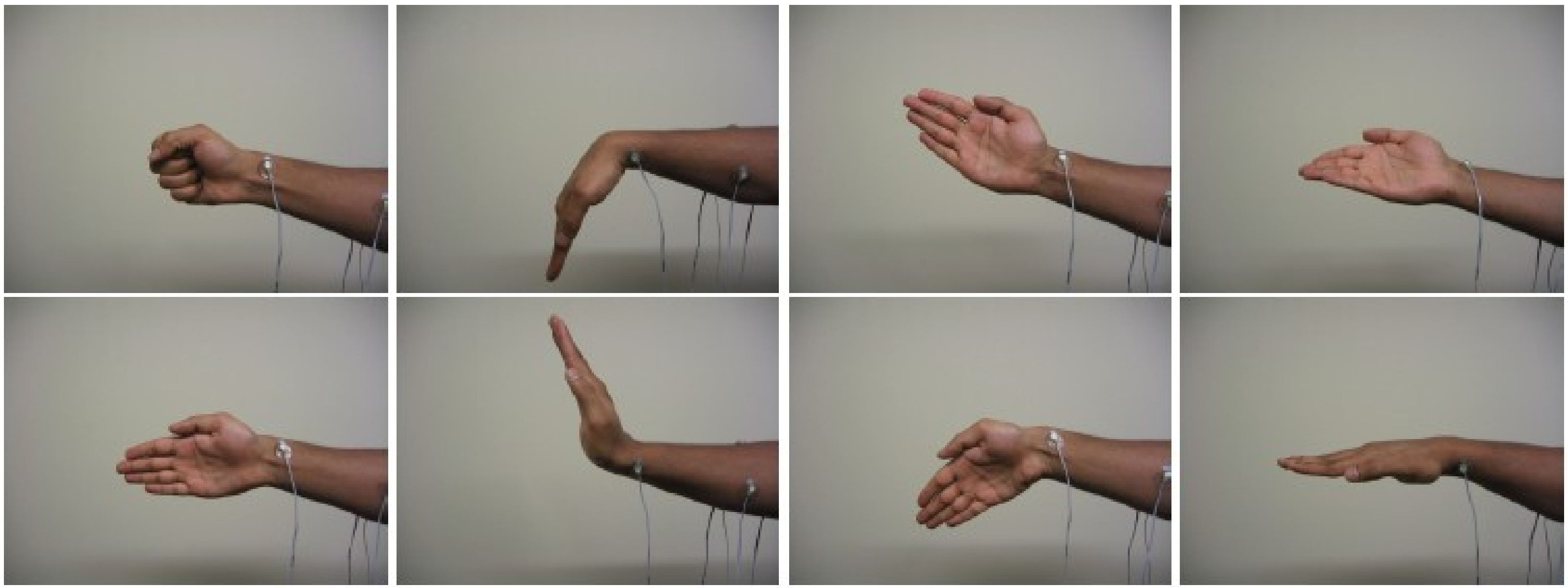
Challenge III

Pen trajectory decoding from EMG data

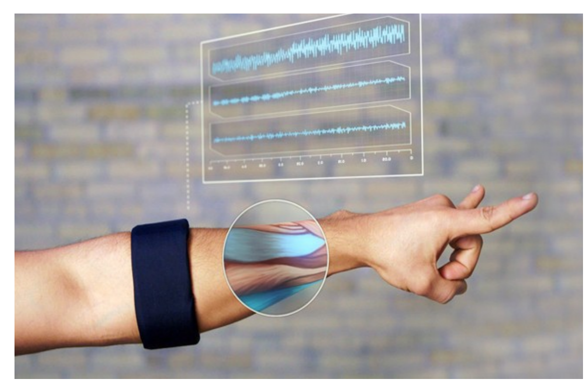
E. Okorokova, M. Lebedev, M. Linderman and A. Ossadtchi (2015). A dynamical model improves reconstruction of handwriting from multichannel electromyographic recordings, Frontiers in Neuroscience, v. 9, 2015, DOI=10.3389/fnins.2015.00389 (baseline solution)

Linderman, M., Lebedev, M. A., and Erlichman, J. S. (2009). Recognition of handwriting from electromyography. PLoS ONE 4:e6791. DOI: 10.1371/journal.pone.0006791 (original solution and data)

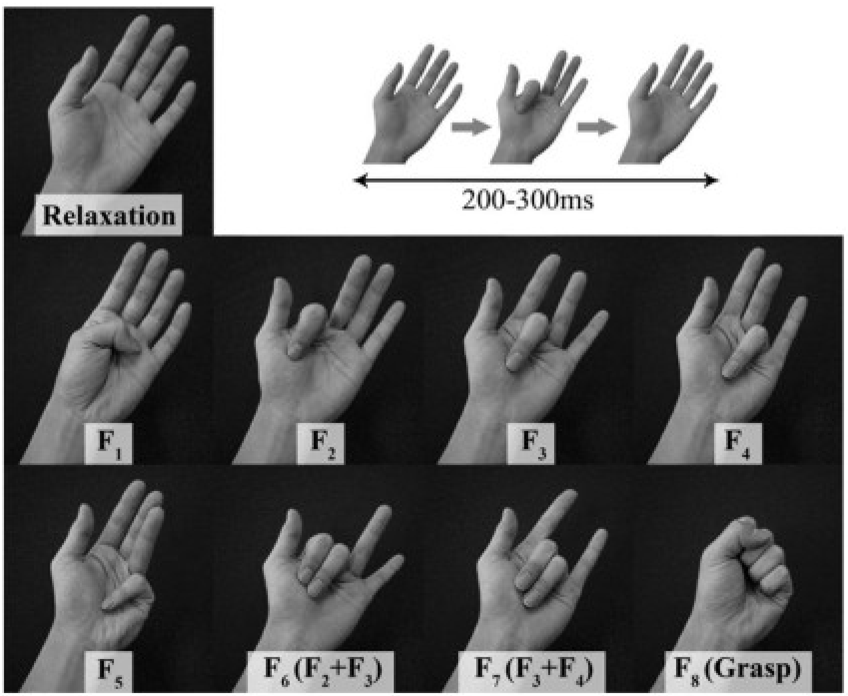
Discrete gesture control = 250 USD

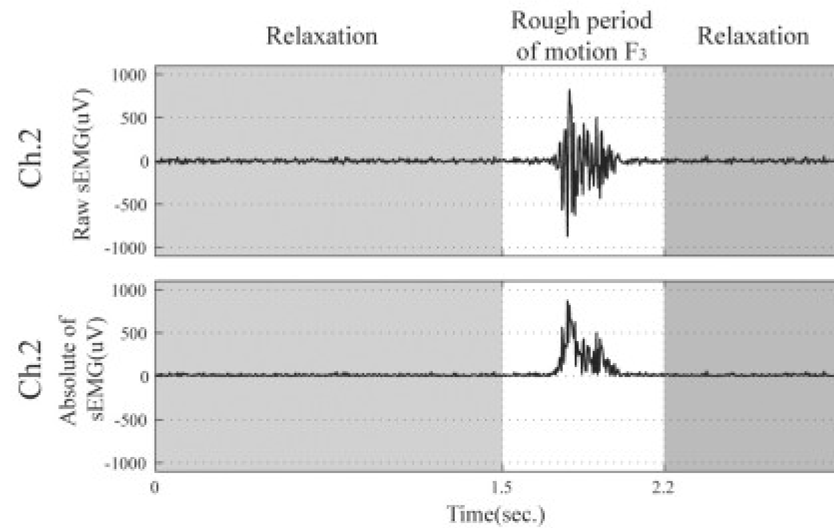


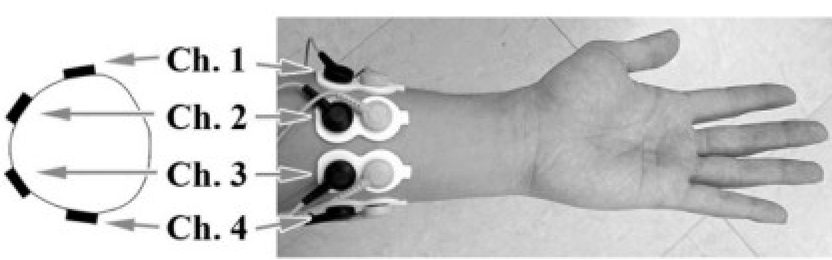
250 USD
@
Yandex\Amazon

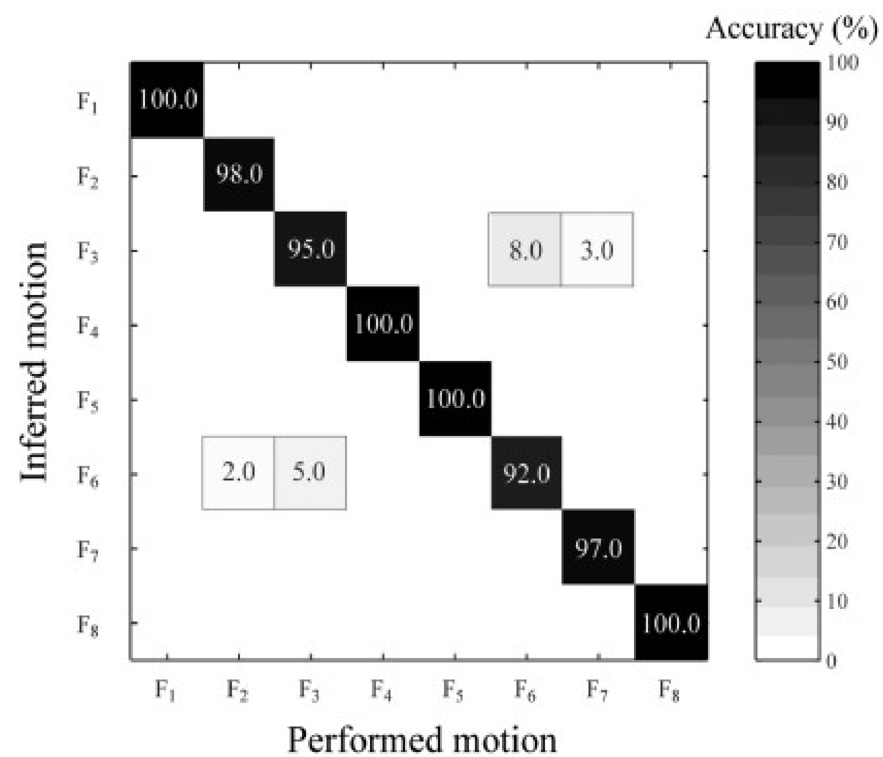


Single finger control

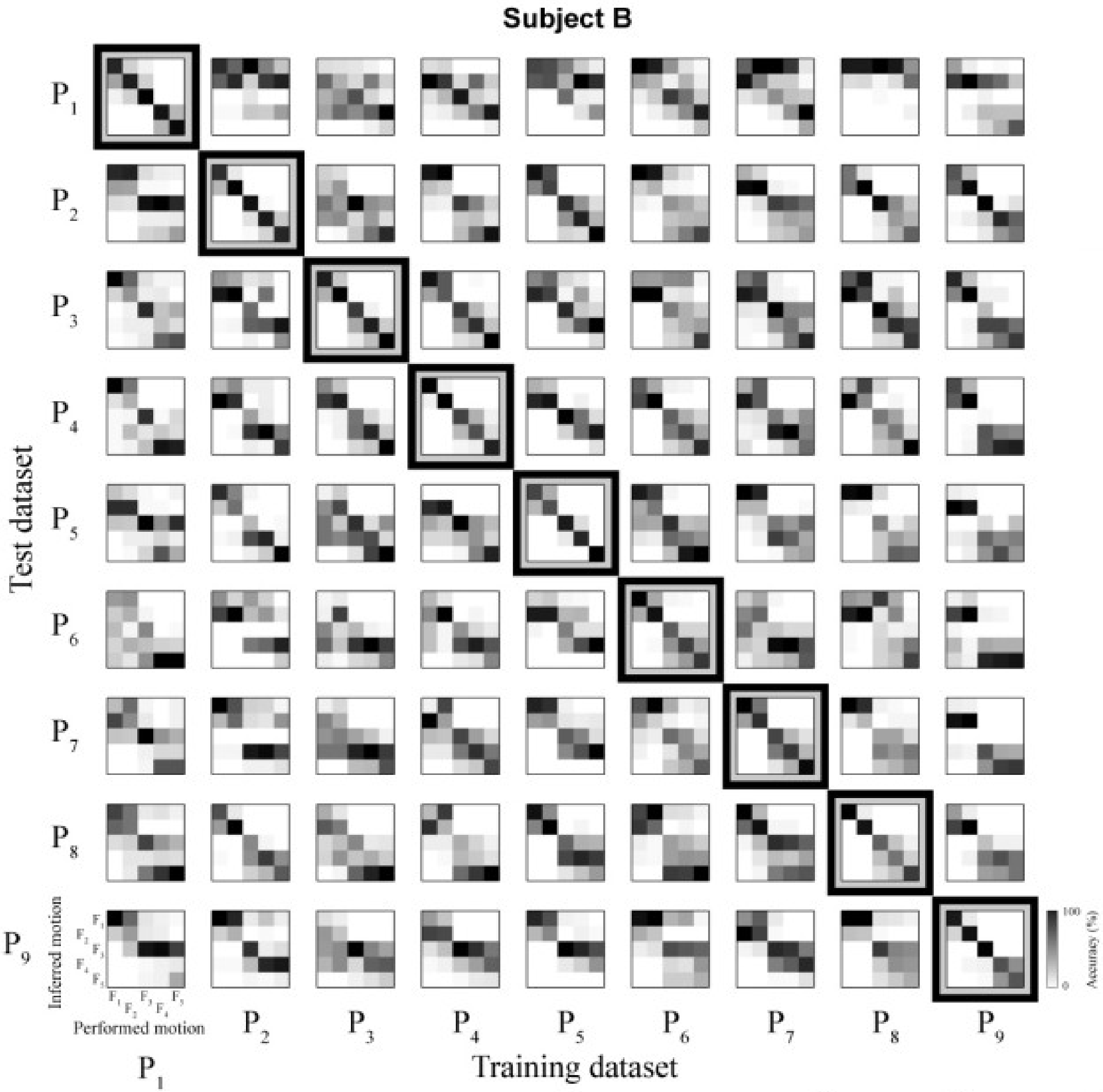


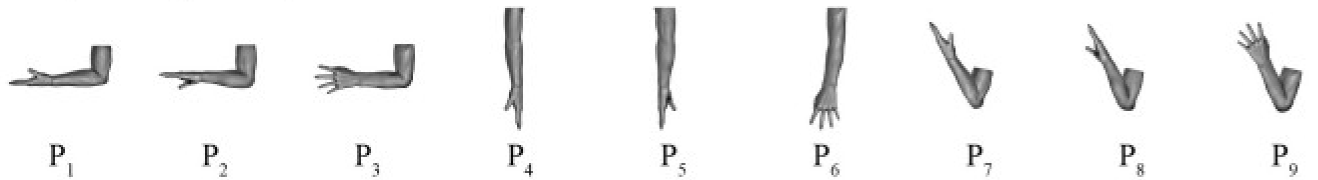






Gets more challenging when different postures are considered





A real challenge

- Continuous decoding of fine grain movements from EMG data
- Universal (starting point) solution that would work on all patients (to be then fine tuned)
- Adaptation to individual patients
- Development of algorithms that “learn as they go”
- This is what task 3 is all about!

In Memoriam

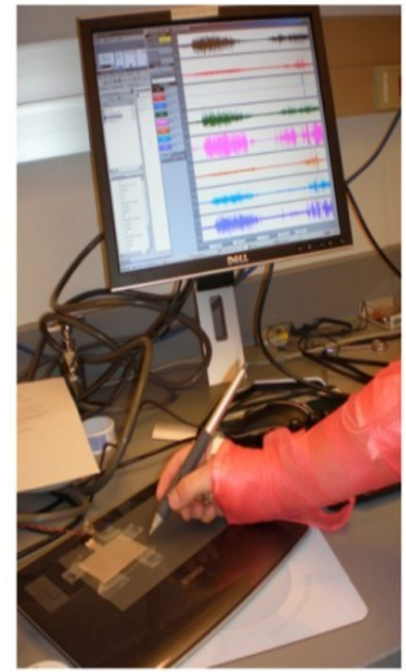
The EMG data used in this contest is the courtesy of Dr. Michael Linderman, our collaborator. Michael Linderman was the founder of Norconnect, Inc, the company that worked in the area of EMG analysis, handwriting recognition, and diagnostics of Parkinson's disease. The company was awarded with grants from National Science Foundation, US Airforce, and Michael J Fox foundation. Michael Linderman authored several patents of his technologies and published several papers in PLOS ONE. **Earlier this year Dr. Linderman died in Canada in a horrible car accident during the routine commute to his office.**

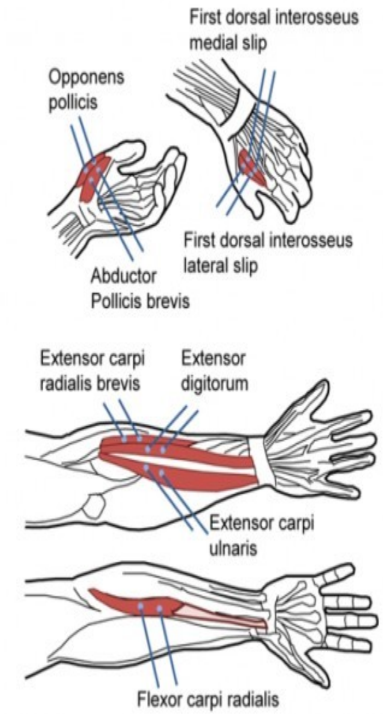
E. Okorokova, M. Lebedev, M. Linderman and A. Ossadtchi (2015). A dynamical model improves reconstruction of handwriting from multichannel electromyographic recordings, Frontiers in Neuroscience, v. 9, 2015, DOI=10.3389/fnins.2015.00389 (baseline solution)

Linderman, M., Lebedev, M. A., and Erlichman, J. S. (2009). Recognition of handwriting from electromyography. PLoS ONE 4:e6791. DOI: 10.1371/journal.pone.0006791 (original solution and data)

Experimental setup & preprocessing

- **Dataset Linderman et al (2009)**
- **3 participants**
- **8 electrodes placed on the leading arm: 4 on the hand and 4 on the forearm**
- **Subjects wrote digits from 0 to 9**
- **Approx. 50 samples of each digit**
- **Envelope extraction**
  •low-pass filter
  •second-order low pass Butterworth filter below 1Hz compute envelope
  •take square root of EMG to account for non Gaussian distribution of the envelopes.
- **Training and testing separation**
  • Half samples used for training the parameters of the model, the rest for cross-validation.

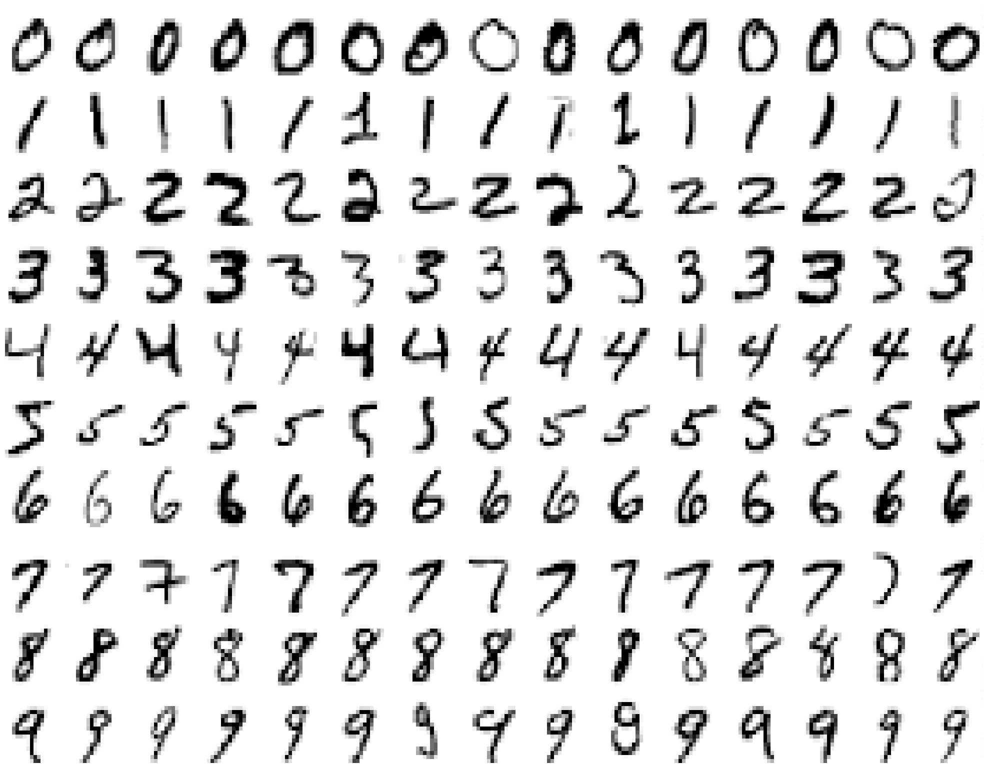


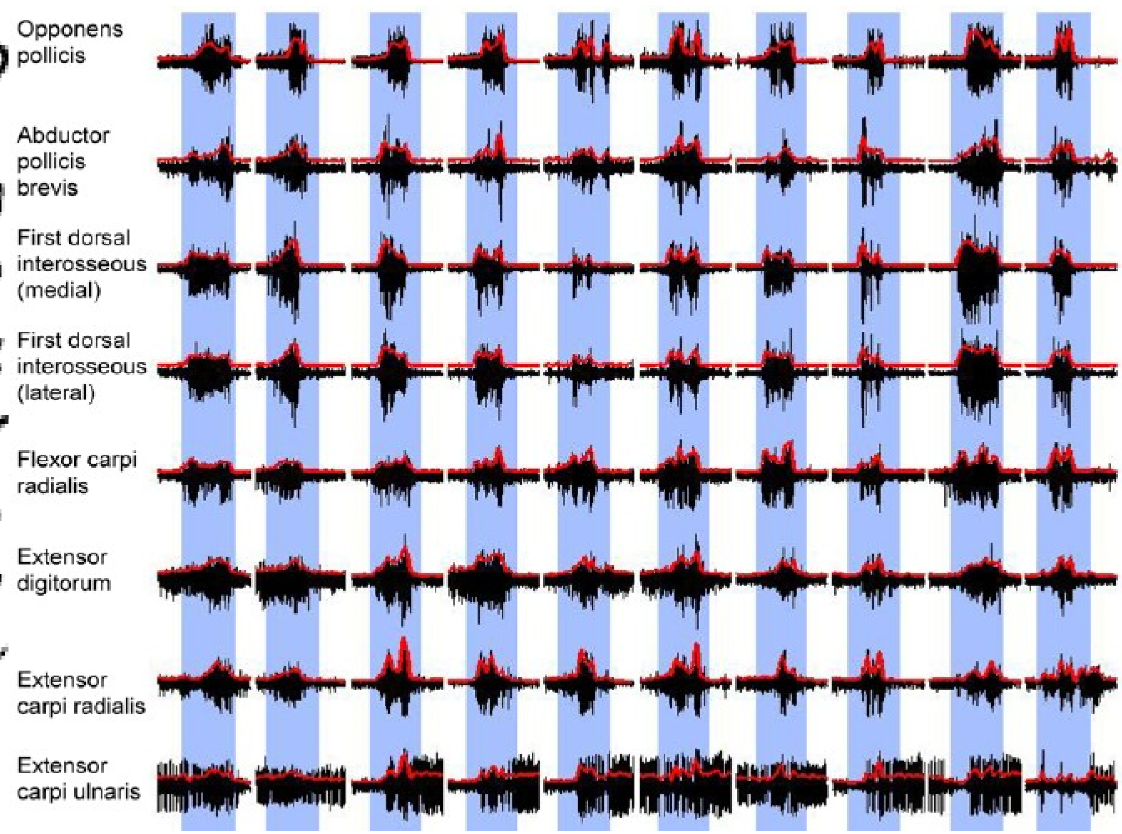


Linderman, M., Lebedev, M. A., and Erlichman, J. S. (2009). Recognition of handwriting from electromyography. PLoS ONE 4:e6791. DOI: 10.1371/journal.pone.0006791 (original solution and data)

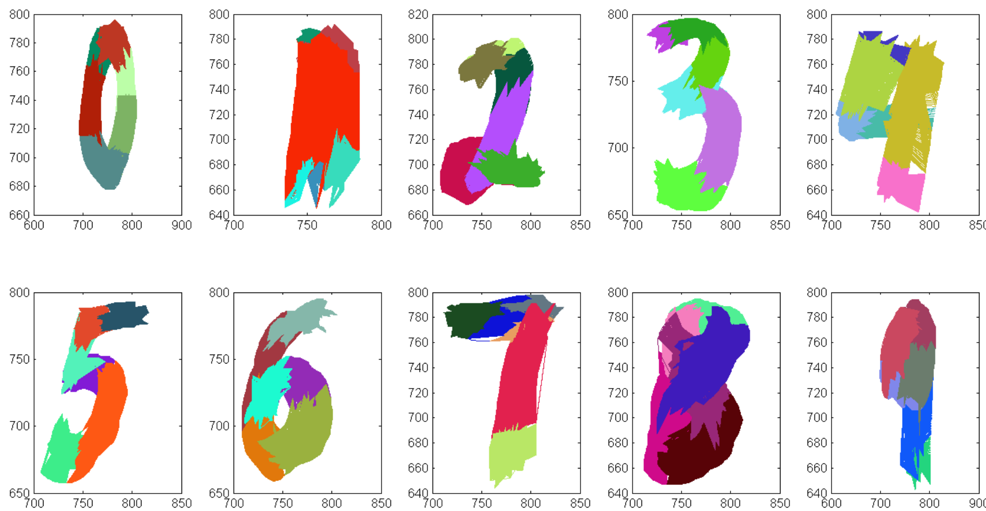
Recorded data

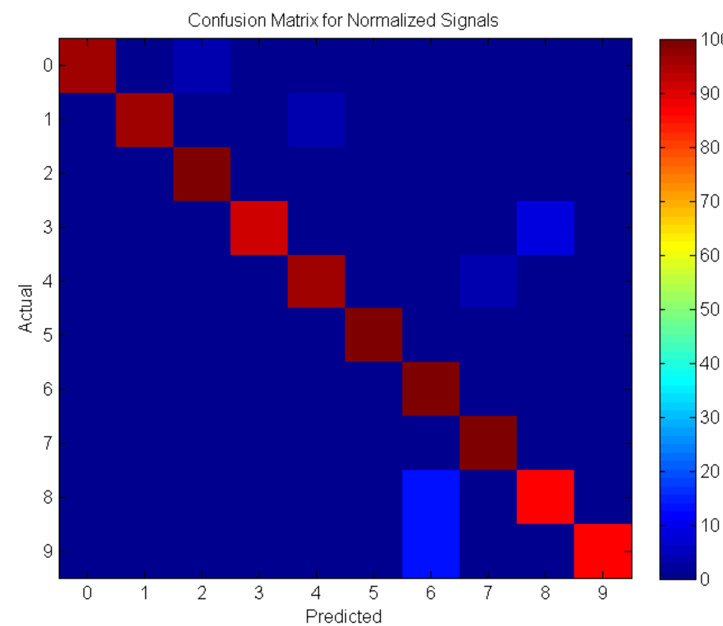
- 8 channel electromyogram (EMG)
- X-Y coordinates of a stylus(pen) recorded on a pad synchronized with EMG
- OnPaper binary signal indicating whether the stylus touched the pad surface

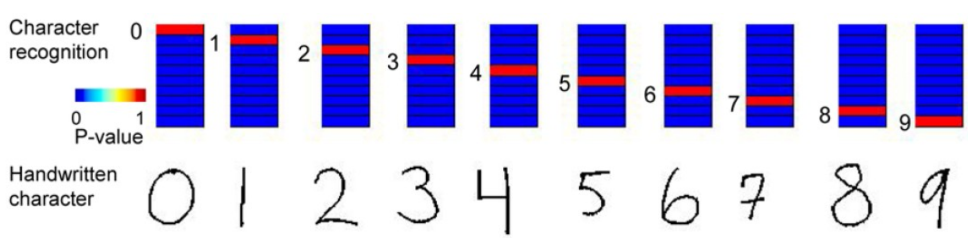




Discrete recognition is not really a trick





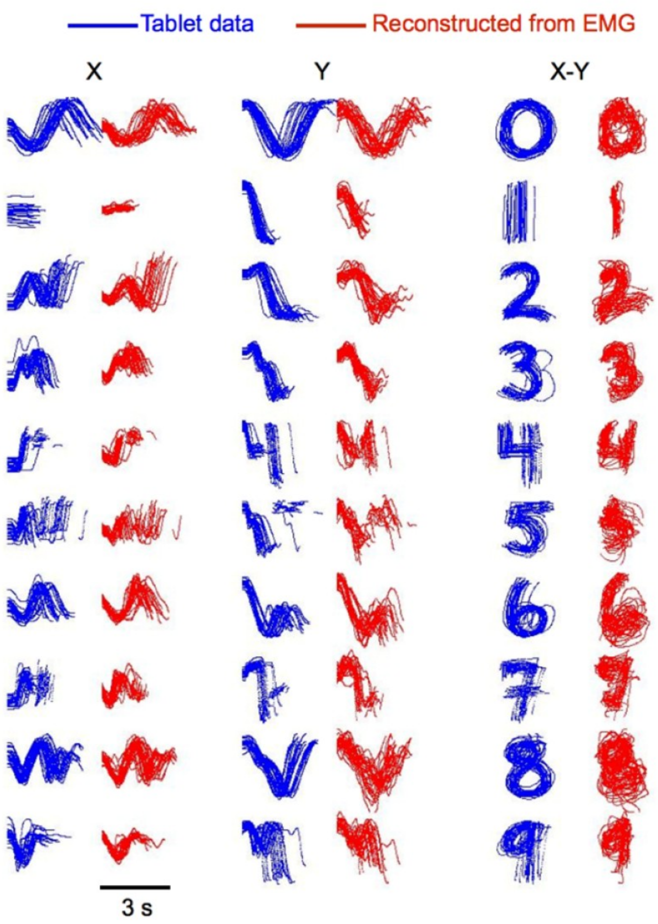


- Hidden Markov Model for finding patterns in the data
- Account for nonlinearity of signals
- Overall average Accuracy: 95.2%

Continuous fine grain EMG-based control

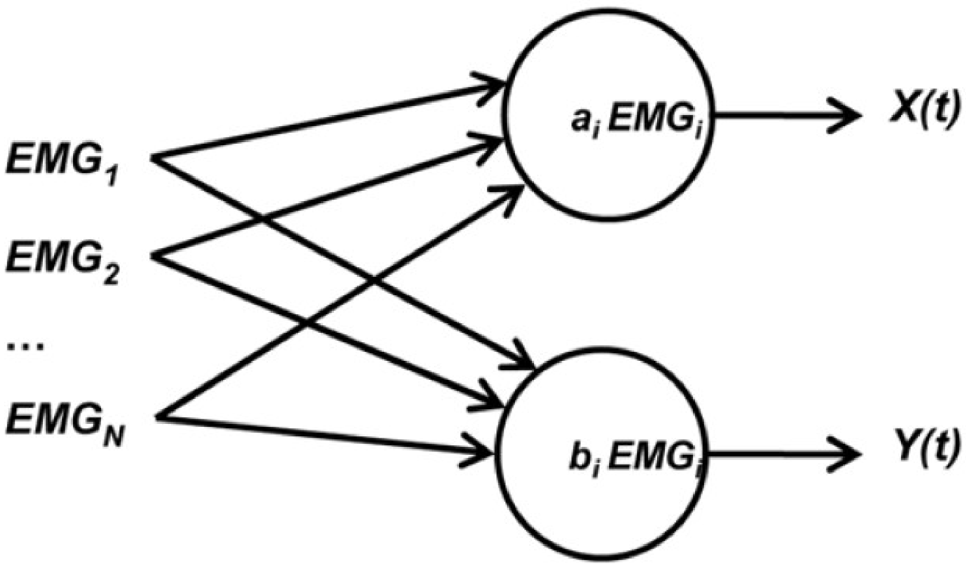
Problem statement: Can we reconstruct the coordinates of the written text based on the ongoing EMG pattern?

Why?
•Immediate feedback to the patient – we don't need to wait until the pattern is fully written and classified
•Can be used in the online-mode for rehabilitation
•Useful for muscle-computer interfaces where immediate response of the system is required
•The first step towards creating naturally controlled wrist prosthetic device



Linderman et.al. 2009

Wiener filter as the simplest solution



- **Exogenous variables**: muscle activity at time interval t
- **Endogenous variables**: Coordinates at time t
- **Objective**: Find such weights ***h*** which provide the min squared error of the objective equation
- **Method**: least squares regression

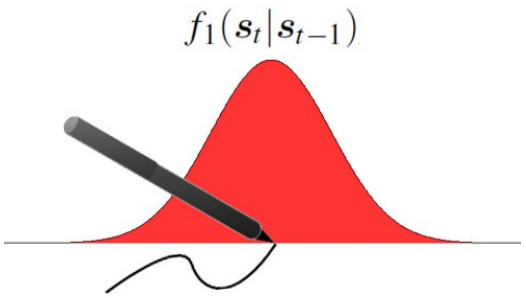
$$s_x(t) = b^x + \sum_{\tau=-T}^{T} (\mathbf{h}_{\boldsymbol{\tau}}^{\mathbf{x}})^T \mathbf{z}(t+\tau)$$

$$s_y(t) = b_y + \sum_{\tau=-T}^{T} (\mathbf{h}_{\boldsymbol{\tau}}^{\mathbf{y}})^T \mathbf{z}(t+\tau)$$

Solve in the least squares sense to find ***b*** and ***h***

Linderman et.al. 2009

Kalman filter solution (baseline)



$$\boldsymbol{s}_t = \boldsymbol{A}\boldsymbol{s}_{t-1} + \boldsymbol{v}_t$$

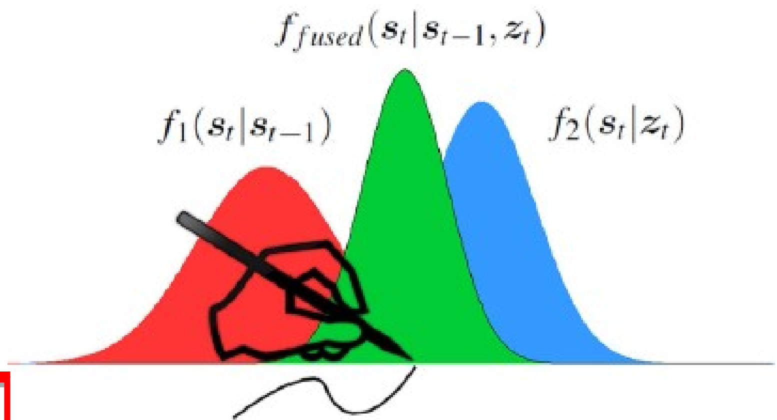
The dynamical model
forecast and error
(covariance matrix):

$$\mu_{1t} = A\mu_{1(t-1)}$$

$$\Sigma_{1t} = A\Sigma_{1(t-1)}A^T + Q$$

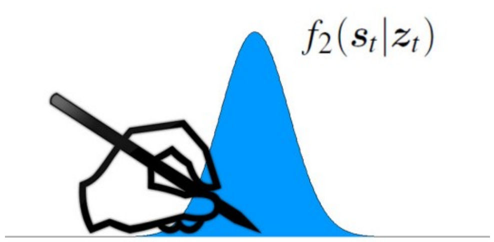
The Kalman Gain:

$$\boxed{K_t = \Sigma_{1t}(\Sigma_{1t} + \Sigma_{2t})^{-1}}$$



$$\boxed{\begin{aligned} \mu_{fused} &= (I - K_t)\mu_{1t} + K_t\mu_{2t} \\ \Sigma_{fused} &= \Sigma_{1t} - K_t\Sigma_{1t} \end{aligned}}$$

The magic of the
Kalman Filter is here



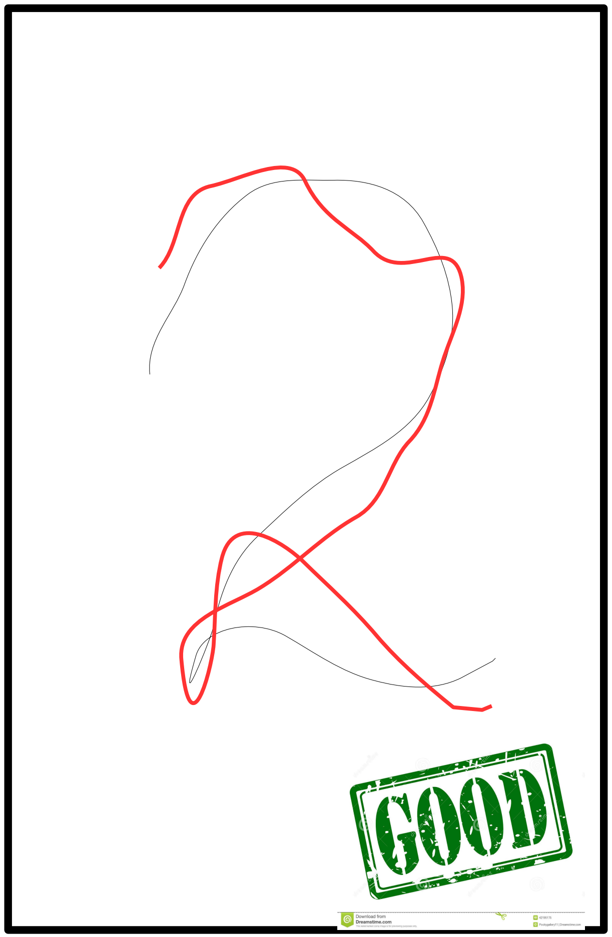
$$\boldsymbol{s}_t = \boldsymbol{H}\boldsymbol{z}_t + \boldsymbol{w}_t$$

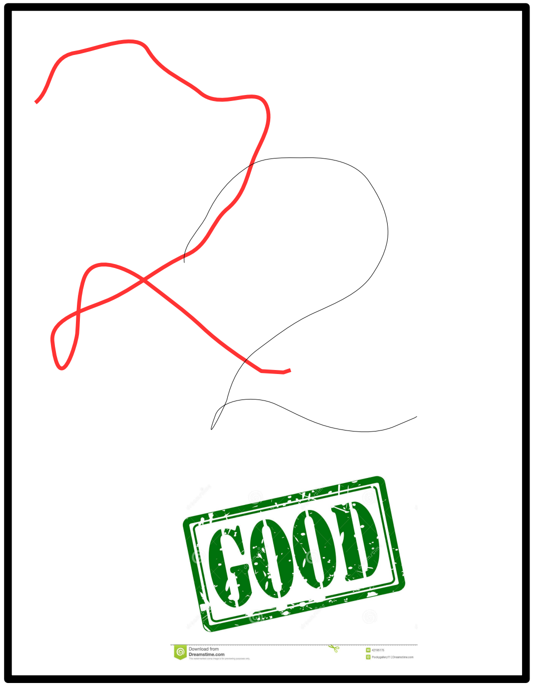
The measurement model
forecast and error:

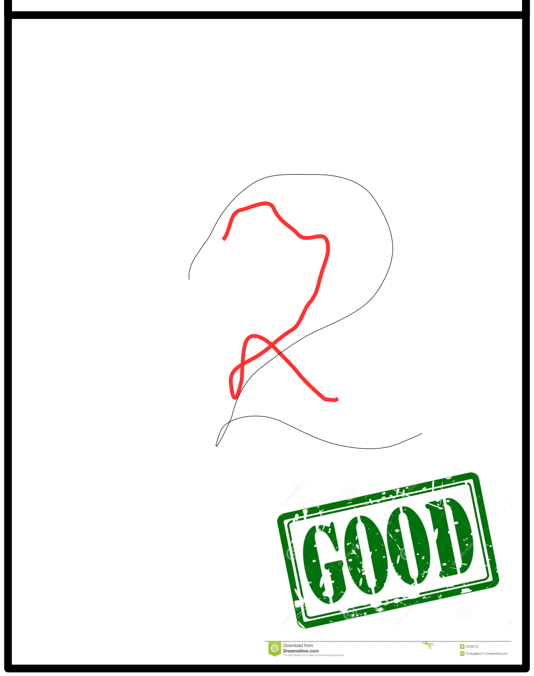
$$\mu_{2t} = E[s_t] = Hz_t$$

$$\Sigma_{2t} = E[w_t w_t^T] = R$$

Motivation for the quality metric







Mean Pearson correlation coefficient

- Scale invariant
- Shift invariant

- Bounded
- Sensitive to rotation

$$d\boldsymbol{x} = \boldsymbol{x}(2:end) - \boldsymbol{x}(1:end-1)$$

Measured trace
x coordinate

Reconstructed trace
x coordinate

$$r_x = \frac{1}{N}\sum_{i=1}^{N} \frac{(d\boldsymbol{x}_i^0)^T d\boldsymbol{x}_i^r}{\sqrt{((d\boldsymbol{x}_i^0)^T d\boldsymbol{x}_i^0)}\sqrt{((d\boldsymbol{x}_i^r)^T d\boldsymbol{x}_i^r)}}$$

$$r_y = \frac{1}{N}\sum_{i=1}^{N} \frac{(d\boldsymbol{y}_i^0)^T d\boldsymbol{y}_i^r}{\sqrt{((d\boldsymbol{y}_i^0)^T d\boldsymbol{y}_i^0)}\sqrt{((d\boldsymbol{y}_i^r)^T d\boldsymbol{y}_i^r)}}$$

Mean over N trials

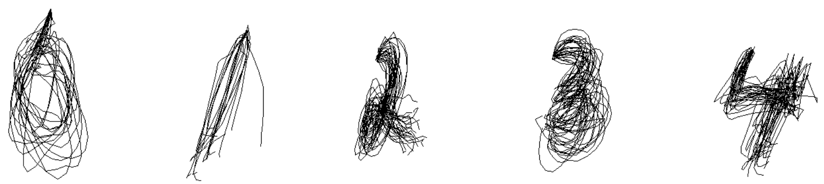
$$\boxed{r_{xy} = 0.5(r_x + r_y)}$$

Baseline Results

Learning all digits at once:
The same set of parameters (matrices A, Q, H, R) for all types of symbols.

Average accuracy of reconstruction:

Jan 7 Dataset:
0.5(0.7304(x) +0.6867(y)) = 0.7086



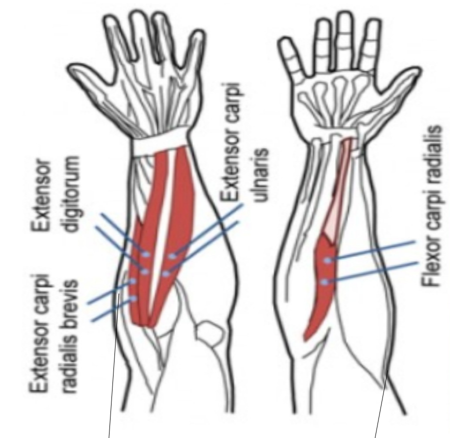
Jan 2 Dataset:
0.5(0.6087(x)+0.5622(y)) = 0.5854

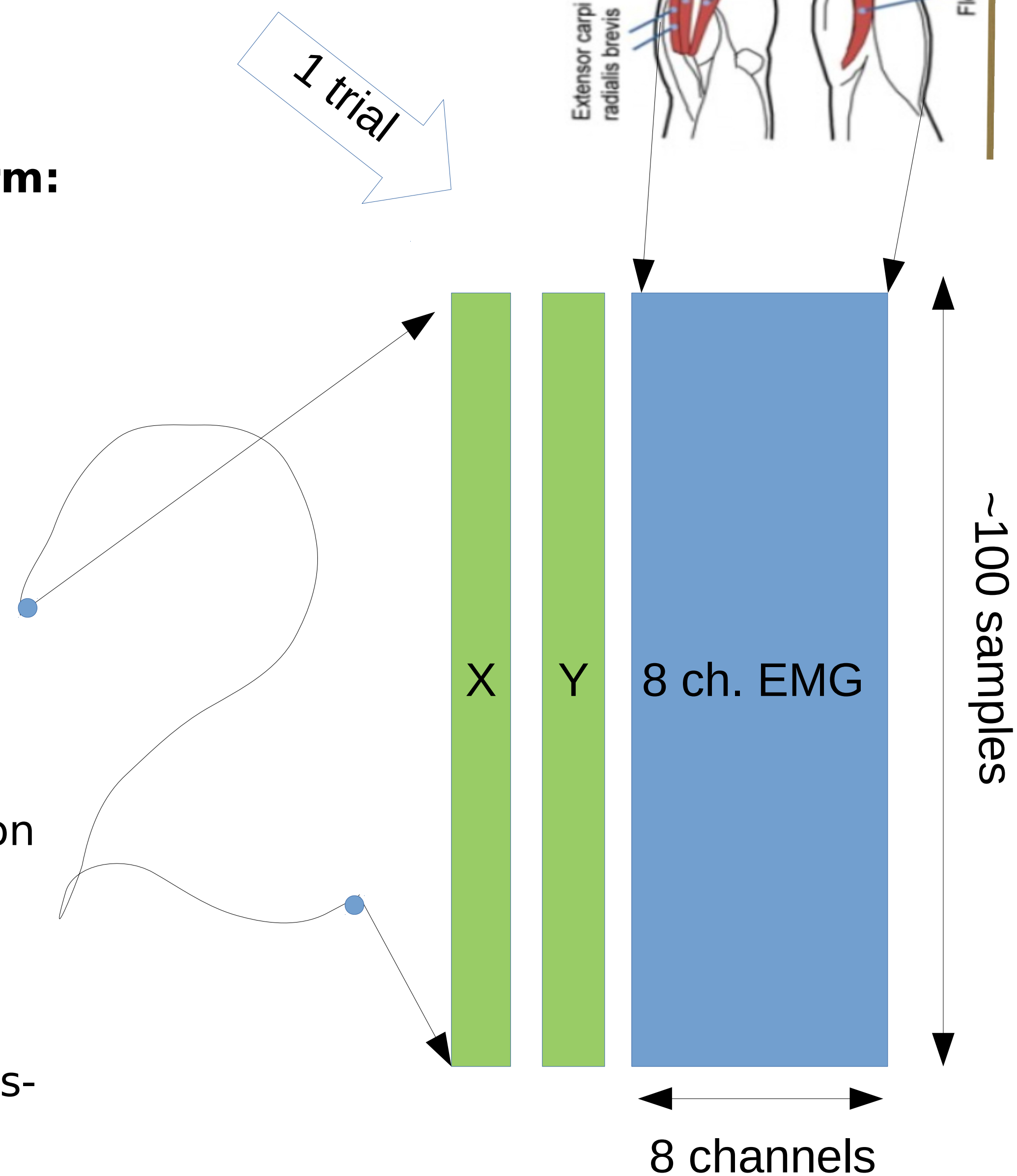
Jan 3 Dataset:
0.5(0.65(x)+0.64(y)) = 0.645

0.6463

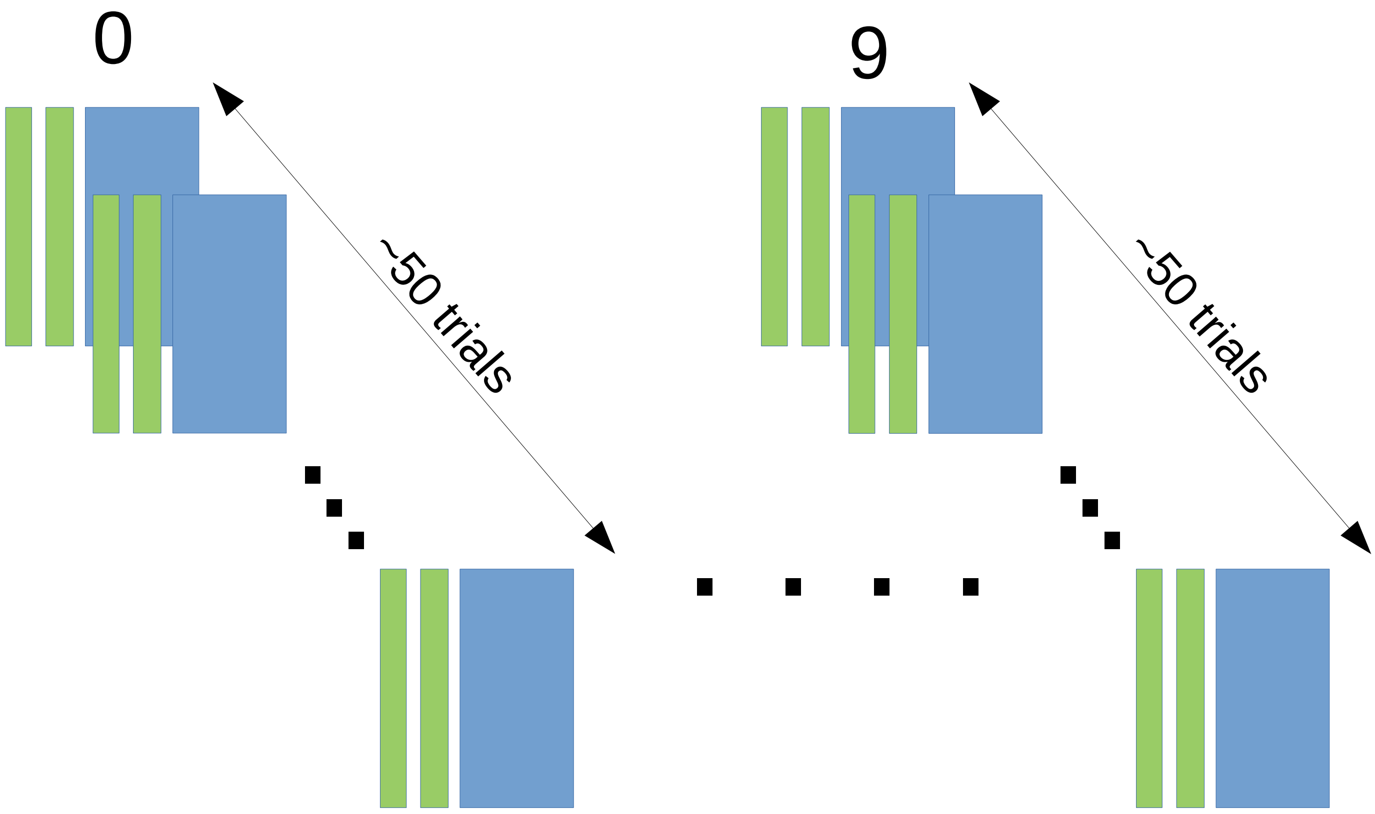
The data I

- **Dataset Linderman et al (2009)**
- **3 participants**
- **8 electrodes placed on the leading arm: 4 on the hand and 4 on the forearm**
- **Subjects wrote digits from 0 to 9**
- **Approx. 50 trilas of each digit**
- **Each trial about 100 time samples**
- **Envelope extraction**
  •low-pass filter
  •second-order low pass Butterworth filter below 1Hz, compute envelope
  •take square root of EMG to account for non Gaussian distribution of the envelopes.
- **Training and testing separation**
  • Half samples used for training the parameters of the model, the rest for cross-validation.



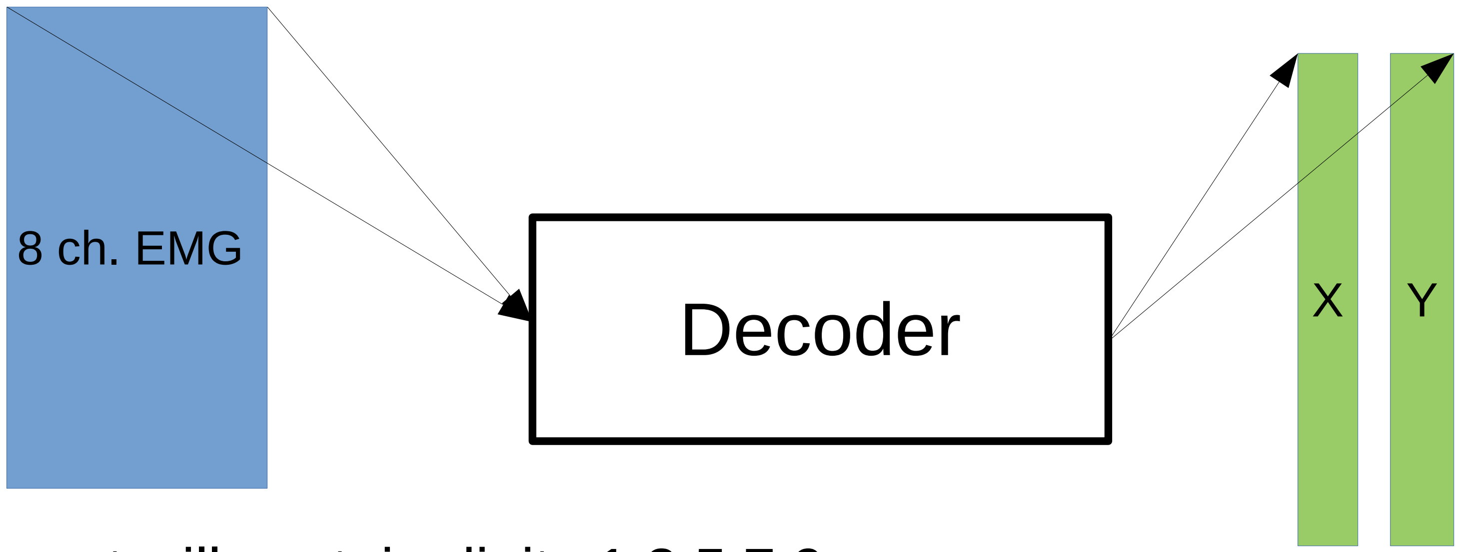


The Data II



x 3 subjects

To do



- Training set will contain digits 1 3 5 7 9
- Testing set will contain digits 0 2 4 6 8
- We are primarily interested in recovery of dynamics from muscle activity data which is the same for the training and testing sets
- You can train a decoder per subject. For the testing data you will know subject's ID
- We are primarily interested in causal analysis, i.e. no EMG samples from the future are available