BCI Technology: Intentional Control and Monitoring of Cognitive States

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Overview of Neurotechnology and Potential Applications

Neurotechology
- machine learning
- adaptive signal processing
- experimental design
- neuroimaging hardware

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Intentional Control

Monitoring cognitive states

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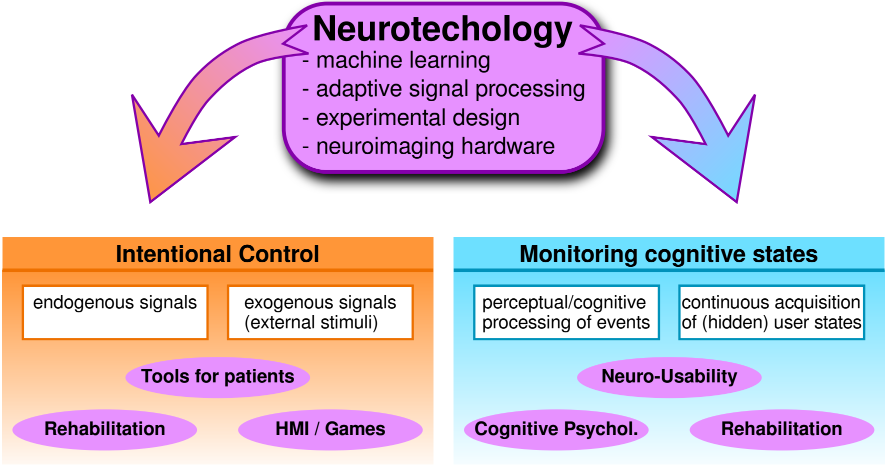
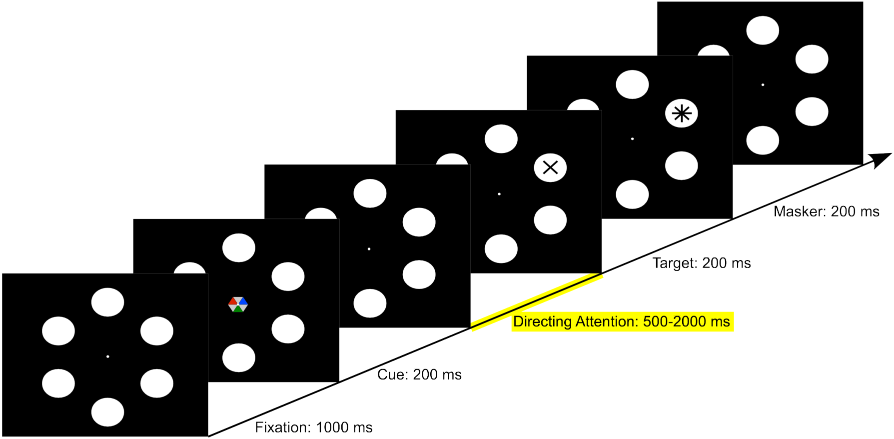


BCIs for Intentional Control

- BCIs based on **endogenous** brain signals
  - Control strategy *motor imagery*
  - Control strategy *covert spatial attention*
- BCIs based on **exogeneous** brain signals
  - Visual Stimuli: From overt to covert attention
  - Auditory Stimuli
  - Multi-modal Stimuli

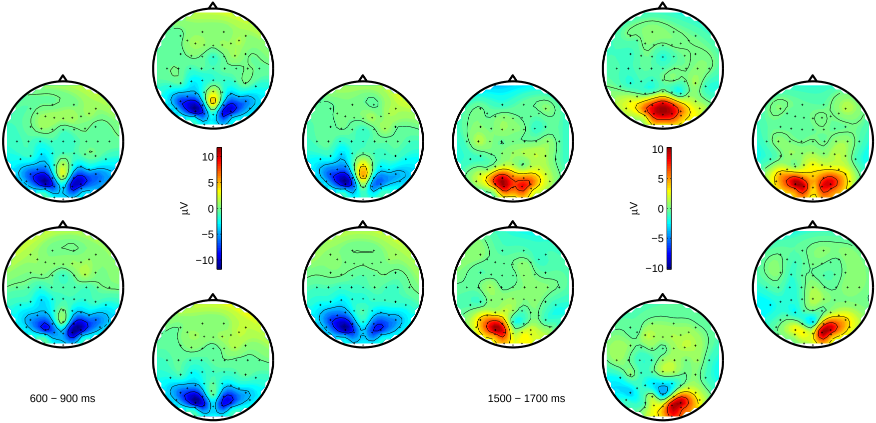
Experimental Design for Covert Shits of Attention

Following the MEG experiment of [van Gerven & Jensen, J Neurosci Methods 2009]:



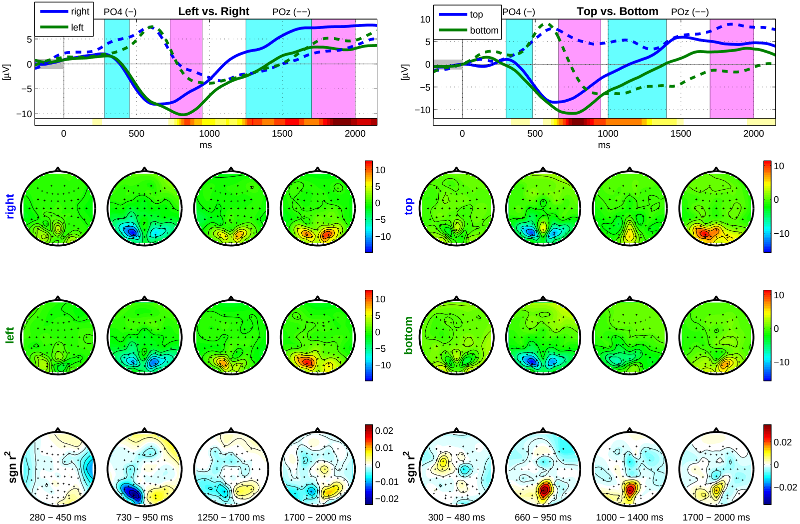
Study with $N = 8$ participants, [Nico Schmidt et al, IEEE SMC 2010].

Topographies of Alpha Modulation



- *Left:* Contralateral Alpha ERD 600–900 ms after cue onset
- *Right:* Ipsilateral Alpha ERS 1700–1900 ms after cue onset

Differential Alpha Modulation (L vs R; top vs bottom)



However, even best the binary classification is only 66 to 87%.

[Matthias Treder et al, J Neuroeng Rehabil 2011]

BCI based on ERPs: The Matrix Speller

Classic example: ***Matrix Speller***

- User concentrates on a symbol
- Rows and columns are intensified randomly
- Target rows and columns elicit specific ERPs (oddball)
- BCI detects target ERPs (averaged over few repetitions)
- Effective communication

[Farwell & Donchin, 1988]

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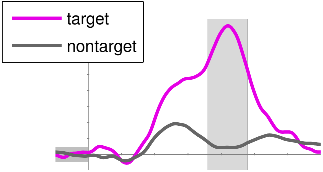

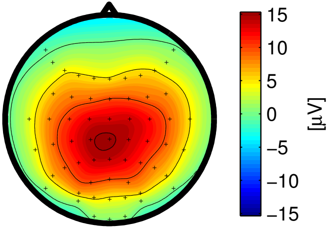

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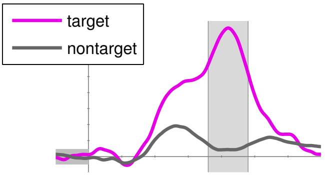
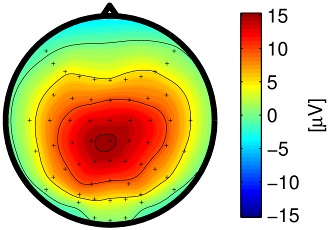




Open Question:

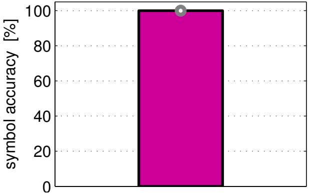
- Role of eye gaze!

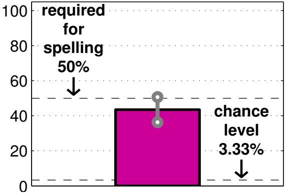
Gaze Dependency of the Matrix Speller

Matrix Speller - Overt

Matrix Speller - Covert

To select **B**: ○ = focus of gaze; ○ = focus of attention





[Treder & Blankertz, BBF 2010]

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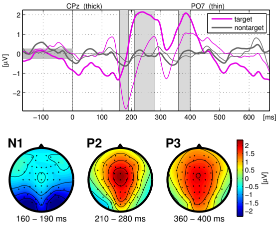

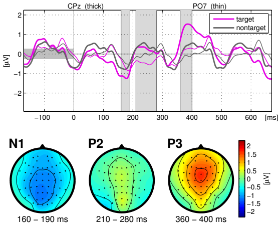

[Treder & Blankertz, BBF 2010] , see also [Brunner et al, JNE 2010].

Conclusions from the Matrix Speller – Gaze Study

- Declining spatial acuity in the periphery and the crowding effect make allocation of covert spatial attention difficult in the Matrix Speller layout.
- Efficient use of the Matrix Speller requires **oculomotor control**.

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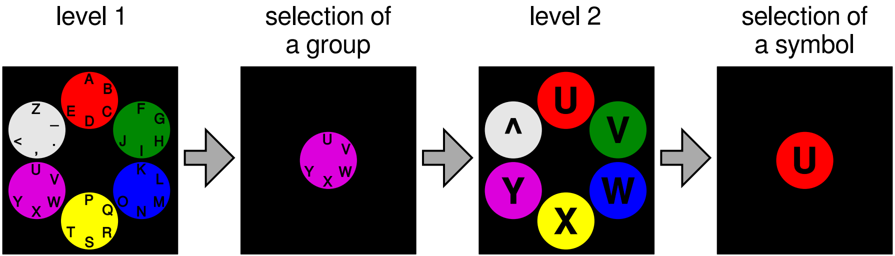
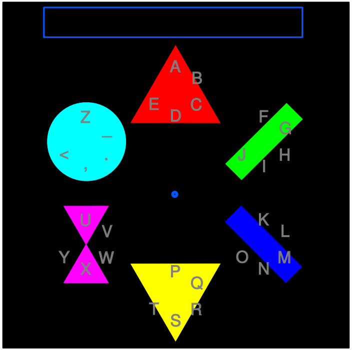
➤ The Hex-o-Spell selection principle:



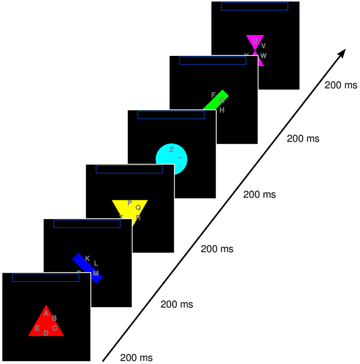
[Matthias Treder & Blankertz, Behav Brain Funct 2010]

Gaze Independent ERP-Speller

Center Speller



Experimental flow



- Two level selection process
- Feature attention (form)
- Feature attention (color)

[Matthias Treder, Schmidt & Blankertz, J Neural Eng 2011]

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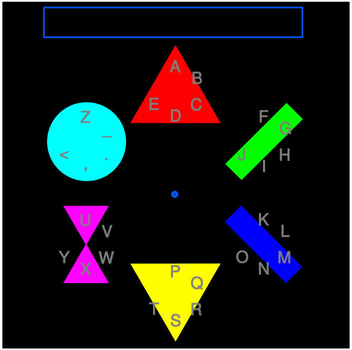

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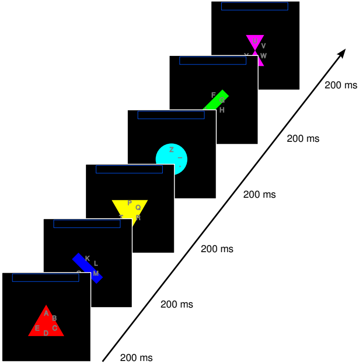

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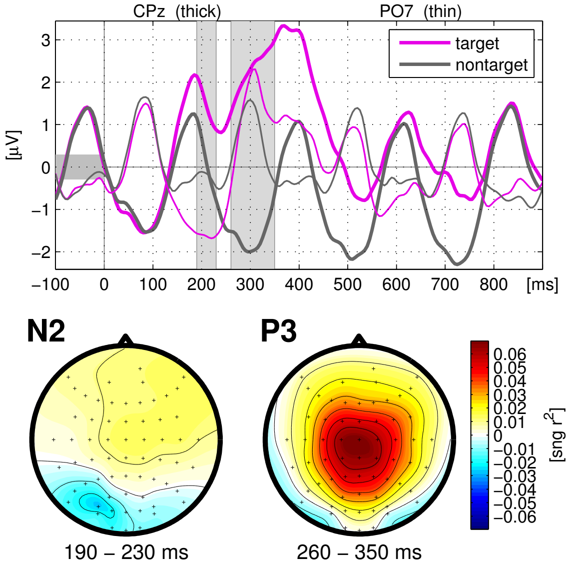
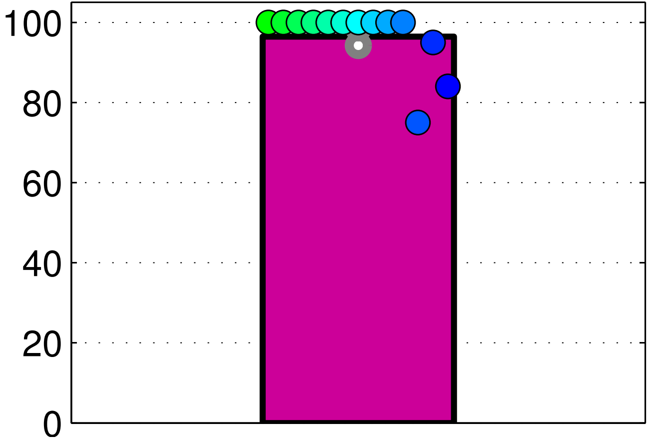
Center Speller: Results - ERPs



Results - Online Spelling Performance

Online symbol selection accuracy was 100% for 10 out of 13 participants.

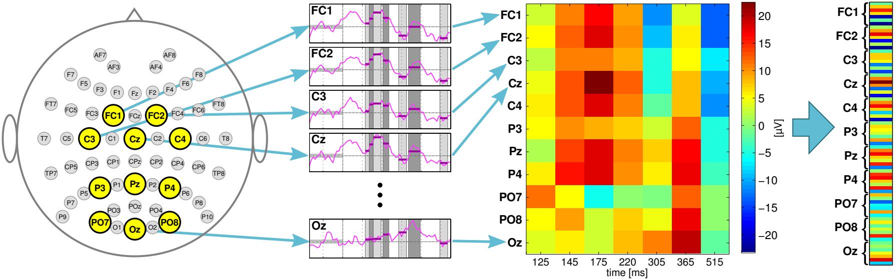


Extraction of Spatio-Temporal ERP Features

Given a set of channels $\mathcal{C}$ and time intervals $\langle \mathcal{T}_i \rangle_{i=1,\ldots,I}$, the *spatio-temporal* feature are defined as

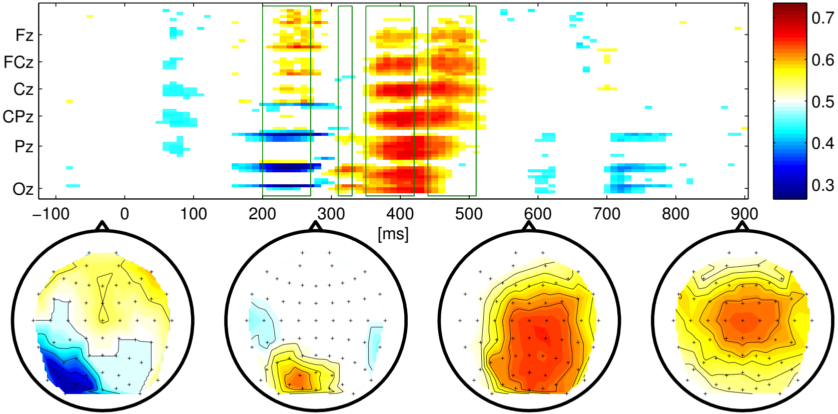
$$\mathbf{X}(\mathcal{C}, \mathcal{T}) = [\text{mean}\, \langle \mathbf{x}_\mathcal{C}(t) \rangle_{t \in \mathcal{T}_1}; \ldots ; \text{mean}\, \langle \mathbf{x}_\mathcal{C}(t) \rangle_{t \in \mathcal{T}_I}].$$

Potentials are averaged within the time intervals, and then the averaged values are concatenated for all intervals and channels.



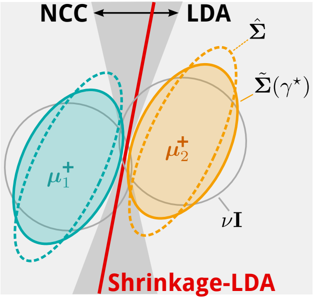
Dimensionality of features: # channels × # intervals

Selection of Time Intervals based on AUC Matrix



- Each cell in the matrix is an uni-variate feature.
- **Time intervals** are chosen by a heuristic based on those values.
- Typically the full set of **channels** is selected.

Classification of Spatio-Temporal ERP Features



Shrinkage-LDA hyperplane is defined by:

$$\mathbf{w} := \tilde{\mathbf{\Sigma}}(\gamma^\star)^{-1}\,(\boldsymbol{\mu}_2 - \boldsymbol{\mu}_1)$$

$$\tilde{\mathbf{\Sigma}}(\gamma) := (1-\gamma)\hat{\mathbf{\Sigma}} + \gamma\nu\mathbf{I}$$

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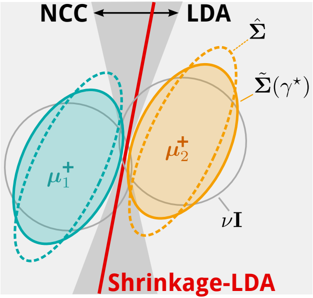

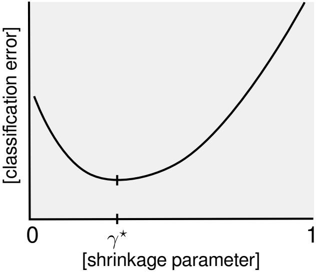

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Calculate optimal $\gamma^\star$ analytically:

$$\gamma^\star = \mathrm{argmin}_\gamma \|\tilde{\boldsymbol{\Sigma}}(\gamma) - \boldsymbol{\Sigma}\|_F^2$$

$$= \frac{n}{(n-1)^2}\,\frac{\sum_{i,j=1}^d \mathrm{var}_k(z_{ij}(k))}{\sum_{i,j=1}^d s_{ij}^2} \quad \text{with}$$

$$z_{ij}(k) := ((\mathbf{x}_k)_i - (\hat{\boldsymbol{\mu}})_i)\,((\mathbf{x}_k)_j - (\hat{\boldsymbol{\mu}})_j)$$

Selection of shrinkage parameter γ:

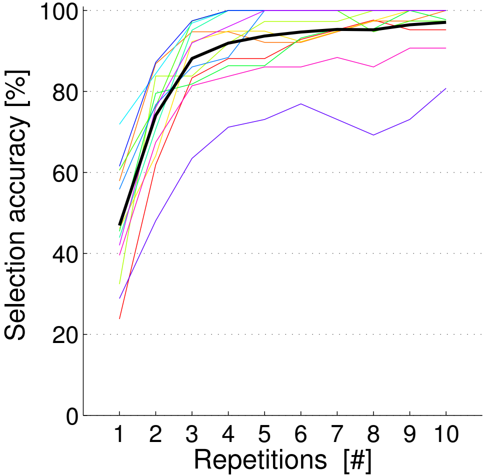
[Ledoit & Wolf 2004], [Schäfer & Strimmer 2005]

Tutorial on ERP classification:

[Blankertz et al, NeuroImage 2011]

BBCI

Results - Simulated Spelling Performance



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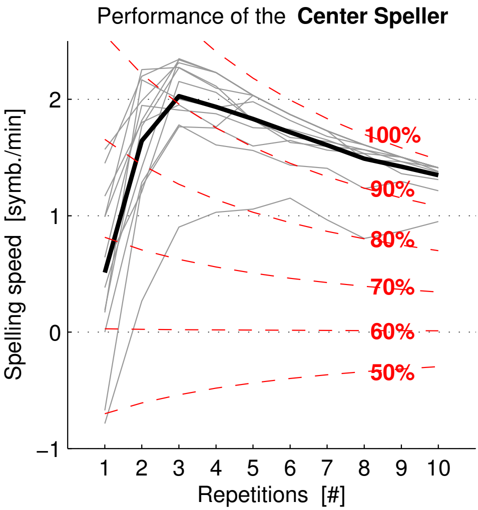
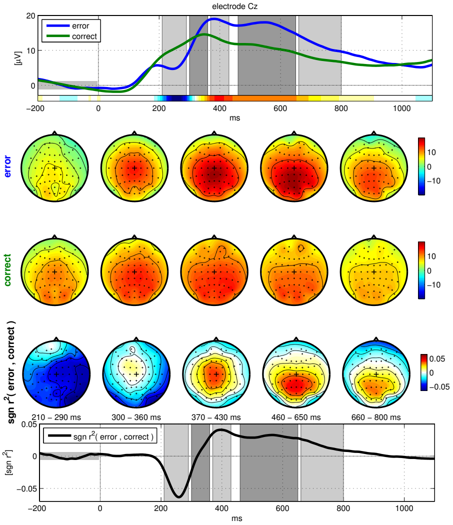


Notes performance measures for spellers: [Blankertz et al, in prep.]

Automatic Response Verification by Error Potentials

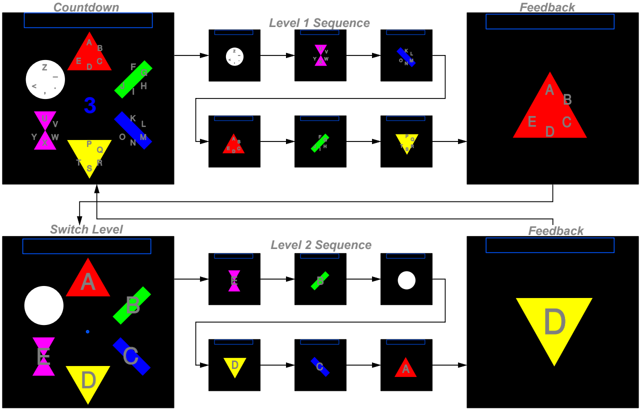


Comparing ERPs after erroneous vs. after correct BCI symbol selection:

- Parietal and occipital (relative) negativation at 200–350ms
- Central positivation at 350–450ms
- Parietal positivation at 500–900ms
- Maps and time course of $sgn\ r^2$-values.

See also [Schalk et al, Clin Neurophysiol 2000; Parra et al, IEEE TNSRE 2003; Ferrez & Millán, IEEE TBME 2008].

Center Speller with Automatic Response Verification



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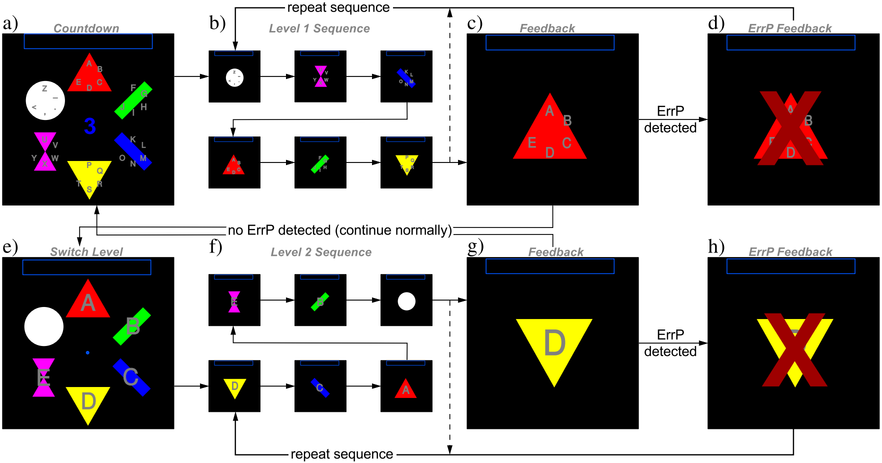
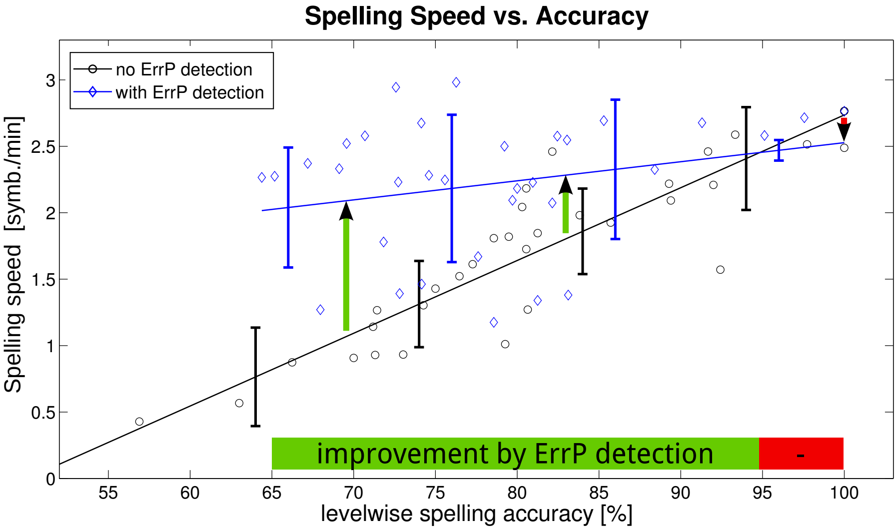
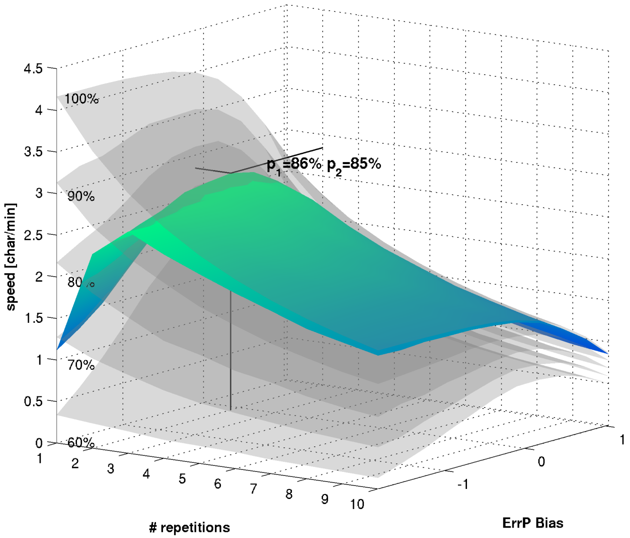


Online Performance of Speller with Response Verification



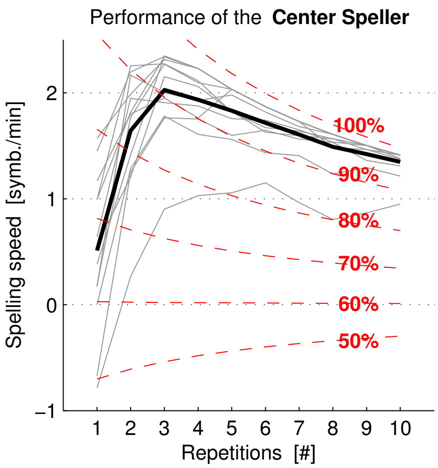
[Nico Schmidt et al, BMC Neurosci 2012]

Trade-off for Spellers with Response Verification



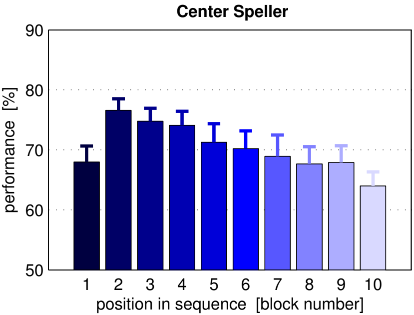
[Blankertz, Schmidt, Treder; in prep]

Reminder: Center Speller - Classification Results



- Is this only an effect of accumulated evidence?
- Can we improve the performance using few repetitions?

All Beginnings are Difficult



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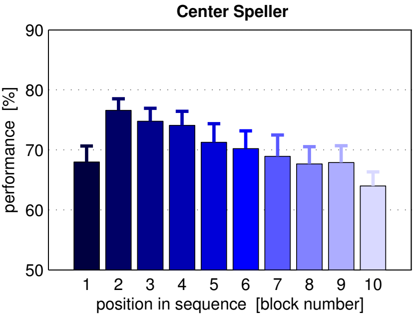

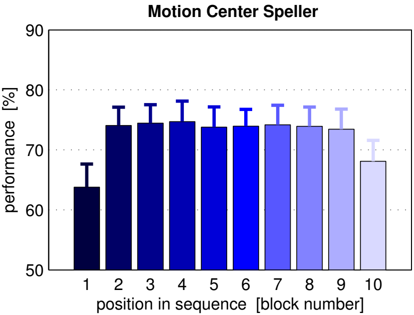

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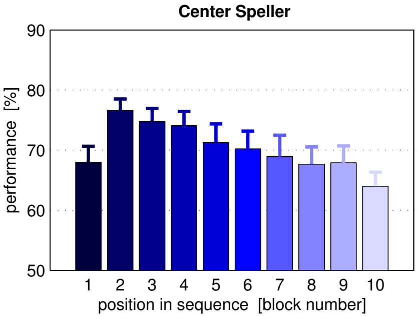

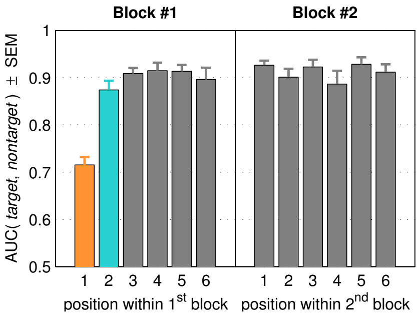

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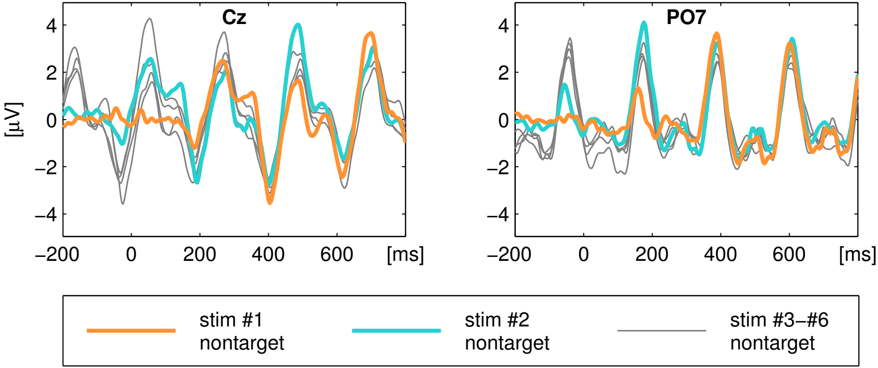
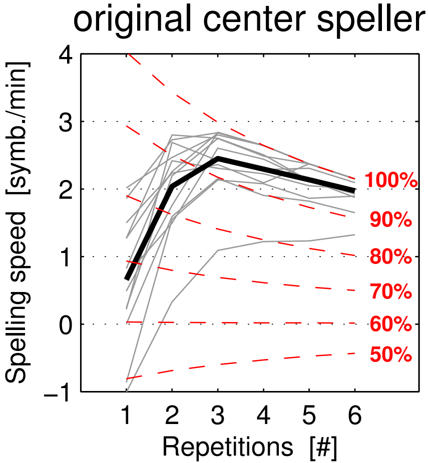


[Blankertz, Schmidt, Treder; in preparation]

Fixing the Block #1 Issue is Crucial for Spelling Speed



Theoretical Extrapolation to Estimate Possible Gain

Let $X \sim \mathcal{N}(\mu_T, \sigma_T^2)$ be the random variable of classifier output to *targets* ignoring rep. #1, and Y for *nontargets*. After averaging classifier outputs cross b blocks (assuming statistical independence), we obtain

$$\bar{X}^{(b)} \sim \mathcal{N}(\mu_T, {}^1\!/_b\, \sigma_T^2) \quad \text{and} \quad \bar{Y}^{(b)} \sim \mathcal{N}(\mu_{NT}, {}^1\!/_b\, \sigma_{NT}^2).$$

We denote the pdf of $\bar{X}^{(b)}$ by $f_{\bar{X}^{(b)}}$ and the cdf of $\bar{Y}^{(b)}$ by $F_{\bar{Y}^{(b)}}$.

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$$P(\bar{X}^{(b)} > \max\{\bar{Y}_1^{(b)}, \ldots, \bar{Y}_{N-1}^{(b)}\})$$

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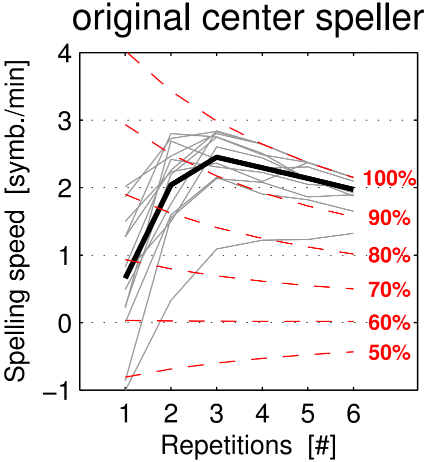
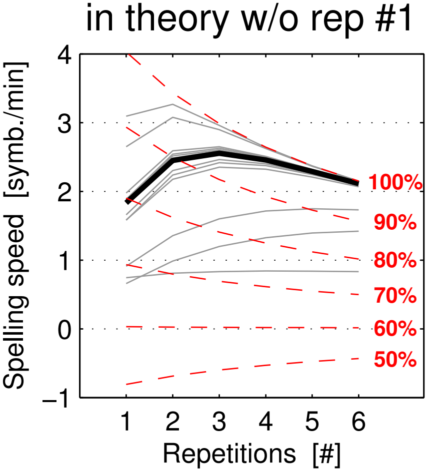
$$\begin{aligned}
&P(\bar{X}^{(b)} > \max\{\bar{Y}_1^{(b)}, \ldots, \bar{Y}_{N-1}^{(b)}\}) \\
&\quad = \int_{-\inf}^{\inf} P(\bar{X}^{(b)} = x \;\&\; \bar{Y}_1^{(b)} < x \;\&\; \ldots \;\&\; \bar{Y}_{N-1}^{(b)} < x)\, dx \\
&\quad = \int_{-\inf}^{\inf} P(\bar{X}^{(b)} = x)\; P(\bar{Y}_1^{(b)} < x)\; \cdots\; P(\bar{Y}_{N-1}^{(b)} < x)\, dx \\
&\quad = \int_{-\inf}^{\inf} f_{\bar{X}^{(b)}} F_{\bar{Y}^{(b)}}^{N-1}\, dx
\end{aligned}$$

➤ This can easily be calculated nummerically.

Merit of Simple Remedy With Preflashes





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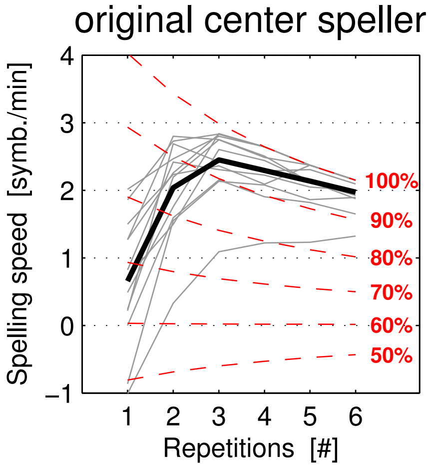
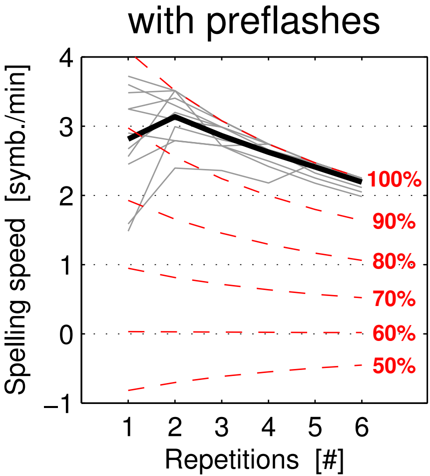
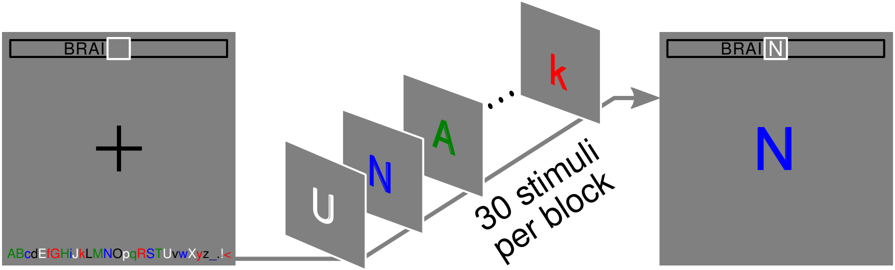




➤ Synchronized preflashes during last second of countdown

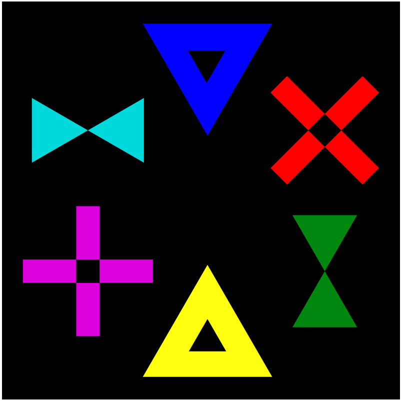
An Alternative: The RSVP Speller

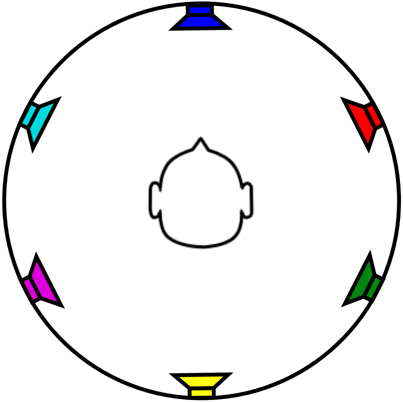
All symbols are displayed in rapid succession (**SOA 83 ms**) at the center of the screen.



[Laura Acqualagna & Blankertz, Clin Neurophysiol, in press]

Novel Auditory Approach for BCI Spelling





Spatial auditory attention

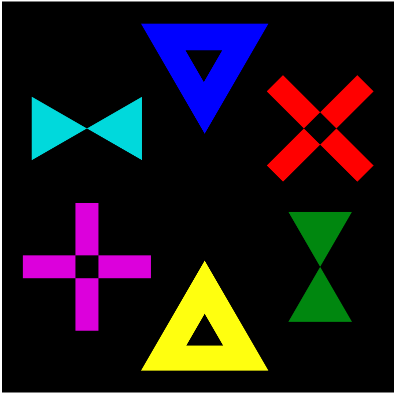
[Martijn Schreuder et al, PLoS One 2010]

[Schreuder et al, Front Neuroscience 2011]

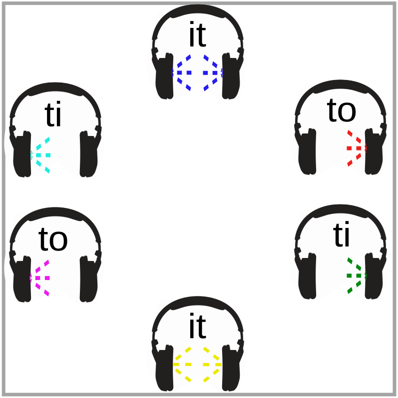
Setup for Spelling with Spatial Auditory Attention

Gaze-Indenpendent Speller Going Multi-Modal

visual stimuli

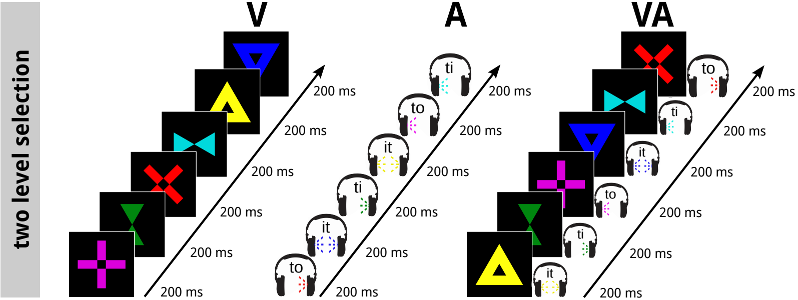


auditory stimuli

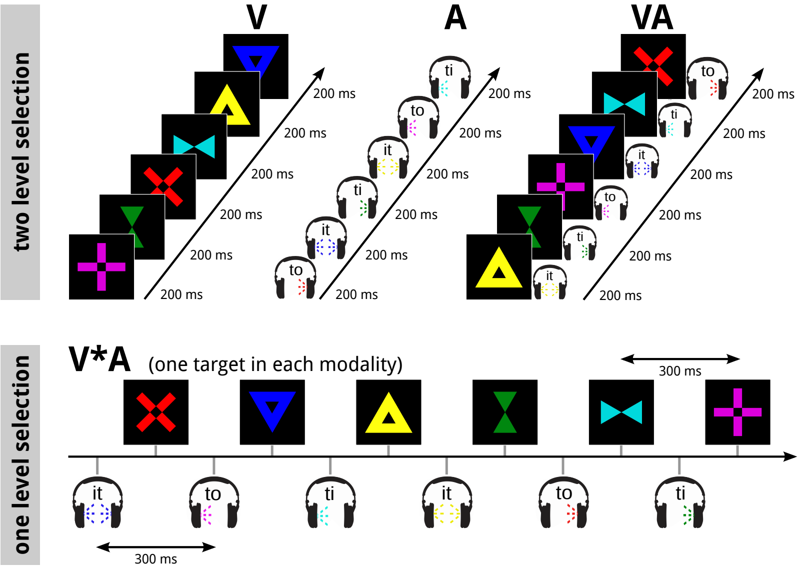


[Johannes Höhne et al, Front Neurosci 2011]

Experiment Flow – Four Conditions

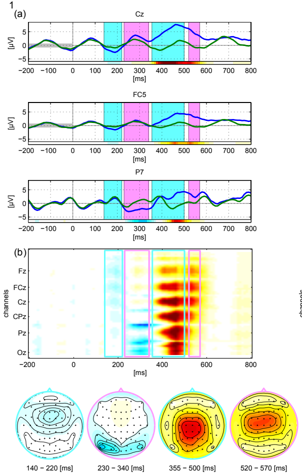


Experiment Flow – Four Conditions

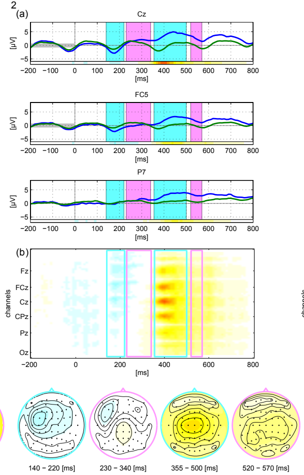


Multimodal Speller Results: GA ERPs for V, A, VA

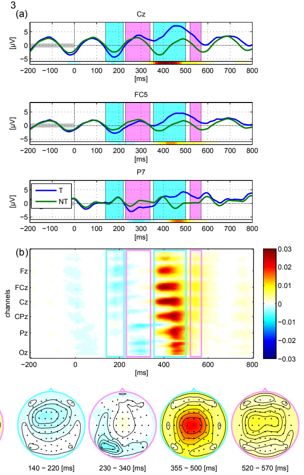
V (visual)



A (auditory)

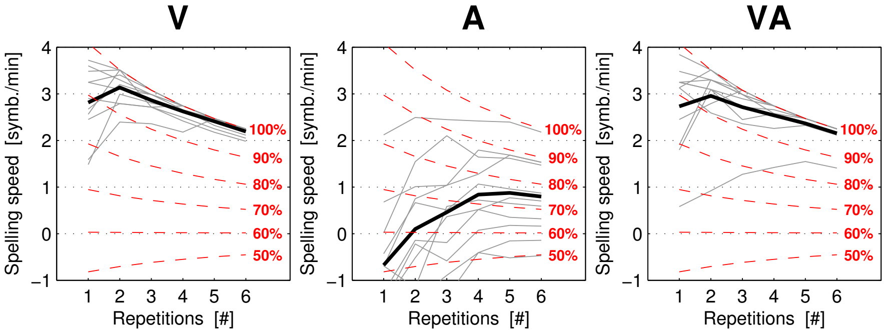


VA (auditory+visual)



[XingWei An, Johannes Höhne & Blankertz; in preparation]

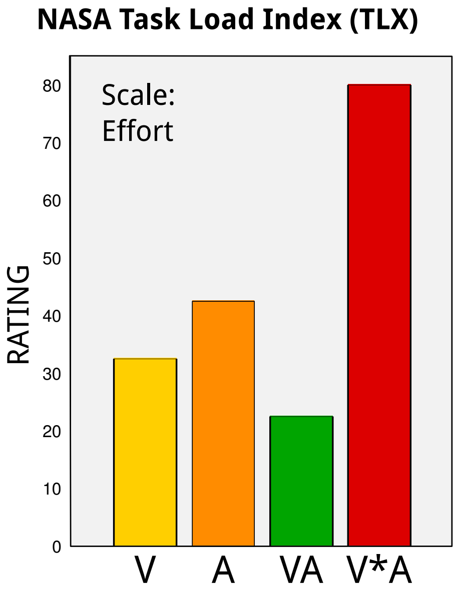
Multimodal Speller Results: Spelling Speed



[XingWei An, Johannes Höhne & Blankertz; in preparation]

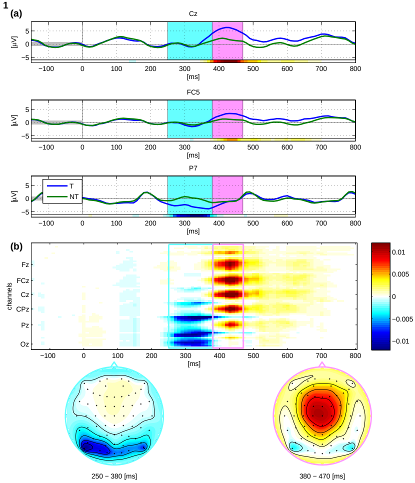
BBCI

What's the Benefit of VA? Less Task Load!

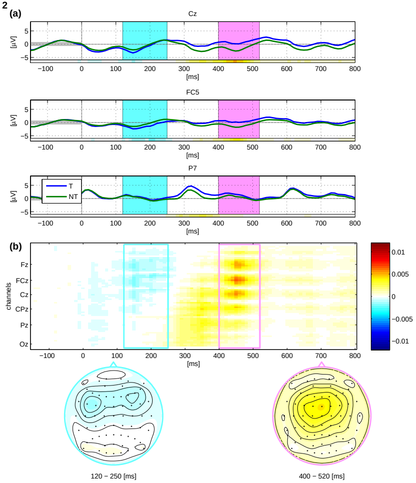


Multimodal Speller Results: GA ERPs for V*A

$\mathbf{V*A|_V}$ (visual cues in V*A)

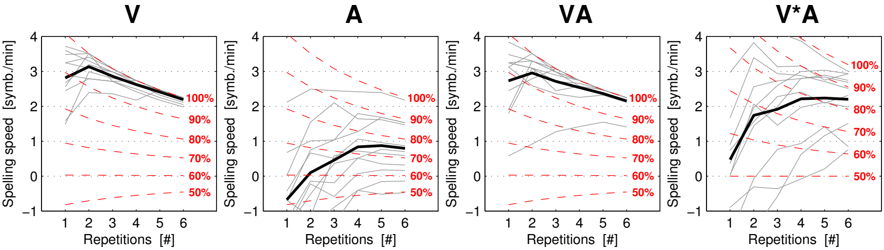


$\mathbf{V*A|_A}$ (auditory cues in V*A)

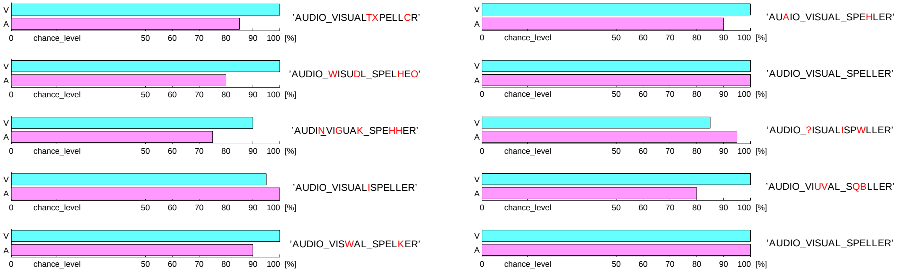


[Note: Different range for colorbar compared to A/V/VA ERP plot!]

Multimodal Speller Results: Spelling Speed



Performance in Online Spelling with V*A (10 Blocks)



[XingWei An, Johannes Höhne & Blankertz; in preparation]

BCI Technology for Monitoring Cognitive States

- Neuro-usability – Assessment of subthreshold auditory perception
  [Anne Porbadnigk et al, IEEE EMBS 2010]
- Neuro-ergonomics – Optimization of Light Sources
  [Anne Porbadnigk et al, IEEE EMBS 2011]
- Cognition of Music – Unconsciously perceived structures of music
  [Irene Sturm et al, in preparation; Blankertz et al, Front Neurosci 2010]
- Car safety – Prediction of emergency braking
  [Stefan Haufe et al, J Neural Eng 2011]
- Tracking of Workload-Induced Modulations of EEG Rhythms
  [Matthias Schultze-Kraft et al, in preparation; Schultze-Kraft et al, BCI Meeting 2013]

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