Dynamic somatosensory perception and the role of pre-stimulus oscillatory activity

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1 Background

Signal detection theory meets perceptual electrophysiology

- Ongoing local α– and β–power used to be candidate signatures for vis. [1] and tact. [2] *sensitivity*
- When catch-trials are included: pre-stimulus α– and β–power both positively associated with *perceptual criterion*: Increased probability for correct rejections and misses [3,4,5] in both domains.

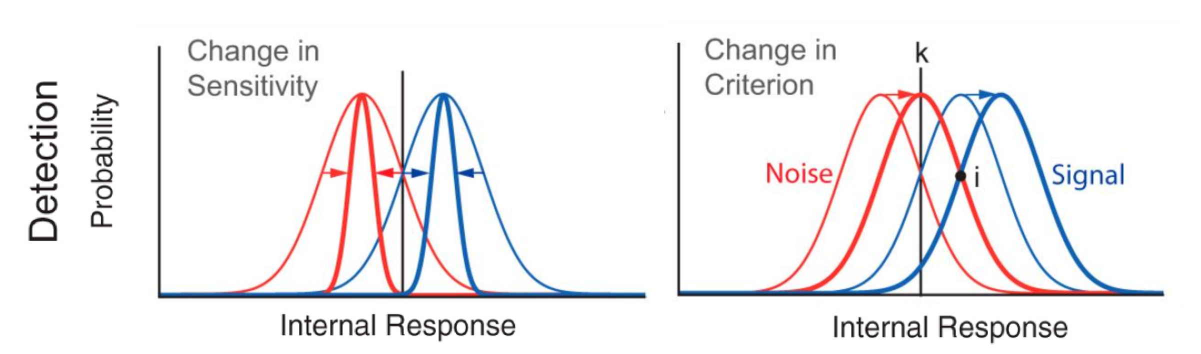


Figure 1 | Possible models of effects on SDT parameters visualized by internal signal and noise distributions. Figure adapted from [3]

Methodological issues

- *Power binning approach* (top vs. bottom 20% narrow-band power): channel-wise univariate testing for differences of behavioral measures per bin (e.g. *HR*, *d'*, *k*…)
  - Inference based on a minority of trials and single channels
  - Disregard of potentially relevant spatial patterns and dynamics

Research question

Which multivariable pre-stimulus neural system states (in particular pre-stimulus neural oscillations) can systematically predict perceived stimulus intensity?

2 Methods

Paradigm

32 young, right-handed males, 1000 trials of tactile stimulation with jittered ISI (1563 ± 50 ms) [6]:

- Clearly detectable electrical stimulation of left median nerve, two *true intensities* (*TI*- vs. *TI+*)
- Immediate motor response with right hand digits, indicating *perceived intensity* (*PI*- vs. *PI+*)

Tactile discrimination task and behavioral results

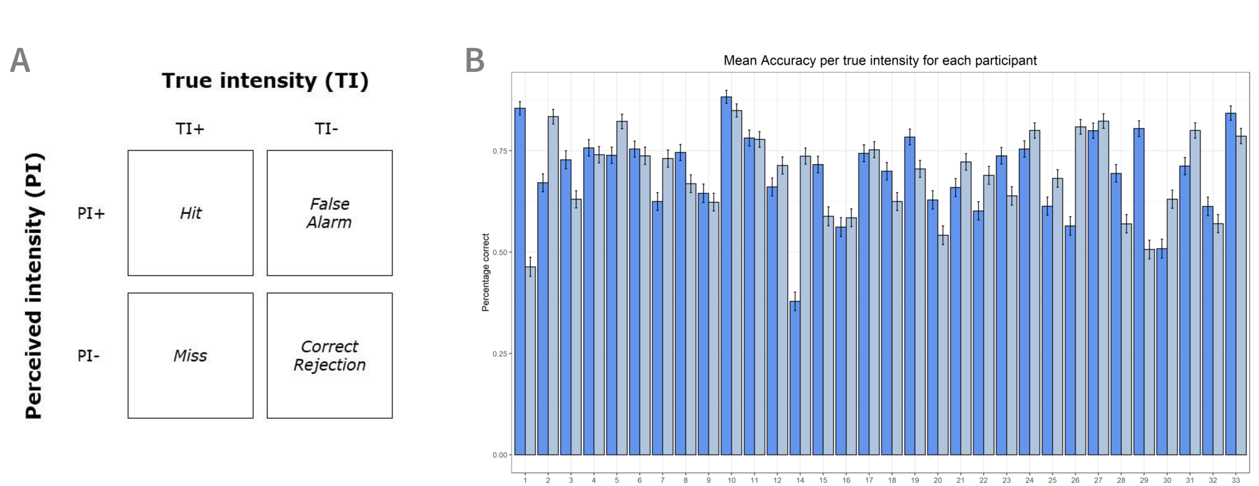
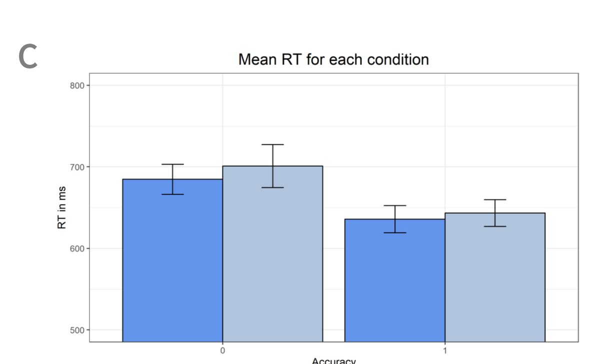


Figure 2 | (A) Confusion matrix for the four response classes in the stimulus discrimination paradigm; (B) Participant-mean accuracy plots, showing clear between-subject variability in receiver operating characteristics; (C) Group-mean condition-wise reaction times for correct and wrong trials, showing the absence of a speed-accuracy trade-off. Error bars denote SEM.



EEG protocol

- *Recording*: 10-10 system EEG + EOG + 2 bipolar electrodes at inner left arm, 5 kHz sampling rate, no online filters
- *Preprocessing*: Interpolation of stimulation artifacts, 4th order Butterworth IIR (1- 200 Hz), visual artifact inspection, infomax ICA with manual removal of ocular and cardiac IC's before inverse ICA, epoching to [-200; -10] ms, trials without reaction discarded

Behavioral analysis

- Error analysis, SAT analysis, Generalized Linear Mixed Modeling (GLMM) of *PI* and *response accuracy* with RT of *previous trial* as a predictor (random intercept and slope, L1: trials, L2: participants, group *z*-standardization, MLE fitting, Wald *t*-tests and Likelihood Ratio Tests for fixed effects).

Multivariate pattern classification

- Target class: *PI* (- vs. +); Separately for pipeline check: motor reaction (pres. vs. abs.) for trial segments of 1st and 3rd RT tertile
- BBCI Toolbox [7]: Participant-wise decoding using LDA with shrinkage, a priori counterbalancing and undersampling, 10-fold cross-validation with nested Common Spatial Pattern (CSP, [8]) analysis: Narrow-band power of min-max 3 CSP-components with largest eigenvalues as features for classifaction. Procedure 3x repeated with permuted labels for statistical testing.
- Statistical testing: Prevalence inference test proposed by Allefeld and colleagues [9]

Linear algebra behind spatial filtering and CSP

EEG data of trial *i* with dimensions *Time* and *Channel* := $\boldsymbol{X}_{(i)} \in \mathbb{R}^{T\times C}$

A spatial fiter $\boldsymbol{w}^{(j)} \in \mathbb{R}^{C}$ projects $\boldsymbol{X}_{(i)}$ into surrogate space:

$\dot{\boldsymbol{x}}_{(i)}^{(j)} = \boldsymbol{X}_{(i)}\boldsymbol{w}^{(j)}$ - which is a column of $\dot{\boldsymbol{X}}_{(i)} \in \mathbb{R}^{T\times J}$ (with $J \leq C$)

This matrix contains *J* **linear combinations** of neural timeseries from all *C* channels. For *C* = *J*: $\boldsymbol{X}_{(i)} = \dot{\boldsymbol{X}}_{(i)}\boldsymbol{W}^{-1}$

Spatial filters can be analytically optimized to increase some SNR!

Find spatial filters that **maximize the variance** of the spatially filtered signal under *one condition* while **minimizing** it for the *other condition.*

Estimate data covariance for condition (*c*): $\hat{\boldsymbol{\Sigma}}^{(c)} \in \mathbb{R}^{C\times C}$

This is usually diagonalizable such that: $\hat{\boldsymbol{\Sigma}}^{(c)} = \boldsymbol{W}^{(c)}\boldsymbol{\Lambda}^{(c)}\boldsymbol{W}^{(c)\top}$

But we want a *common* eigenvector matrix $\boldsymbol{W}$: $\boldsymbol{\Lambda}^{(+)} = \boldsymbol{W}^{\top}\hat{\boldsymbol{\Sigma}}^{(+)}\boldsymbol{W}$

$\boldsymbol{\Lambda}^{(-)} = \boldsymbol{W}^{\top}\hat{\boldsymbol{\Sigma}}^{(-)}\boldsymbol{W}$

$\boldsymbol{\Lambda}^{(+)} + \boldsymbol{\Lambda}^{(-)} = \boldsymbol{I}.$

Consequence: The closer an eigenvalue is to 1 resp. 0, the better a spatial filter separates two conditions based on channel variance (= signal power) for class *(+)* resp. *(-)*!

3 Results

Generalized linear mixed model

Table 1 | Results table for the GLMMs of trial-wise perceived intensity (*PI*) and accuracy (*Acc*) using the *z*-standardized RT of preceding trials as the predictor. All *p*-values based on Wald *t*-tests (equal results for LRTs), 95%-CI: Average reaction times were usually followed by correct responses. Slow trials are more likely to be followed by low *PI* and by incorrect trials.

	PI				Acc			
Predictors	*Odds Ratios*	*CI*	*Statistic*	*p*	*Odds Ratios*	*CI*	*Statistic*	*p*
(Intercept)	0.95	0.86 – 1.05	-1.00	0.316	2.45	2.14 – 2.79	13.35	**<0.001**
RT_prev	0.84	0.78 – 0.91	-4.38	**<0.001**	0.73	0.65 – 0.81	-5.81	**<0.001**
Random Effects								
σ^2	3.29				3.29			
τ_{00}	0.08 $_{ID}$				0.14 $_{ID}$			
τ_{11}	0.04 $_{ID.RT\_prev}$				0.09 $_{ID.RT\_prev}$			
ρ_{01}	-0.29 $_{ID}$				-0.75 $_{ID}$			
ICC	0.04				0.06			
N	32 $_{ID}$				32 $_{ID}$			
Observations	29318				29318			
Marginal R^2 / Conditional R^2	0.008 / 0.044				0.028 / 0.090			

Multivariate pattern classification

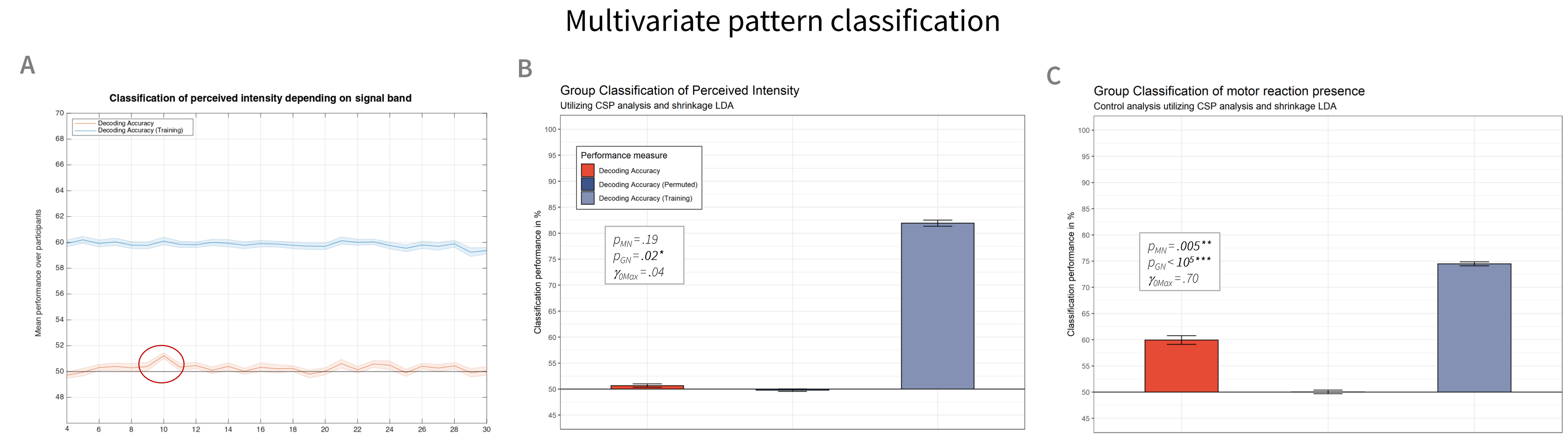


Figure 3 | (A) Mean cross-validated classification performance for each band-pass window: peak at [10 13] Hz; (B) Group-level performance in classification of *PI* using the best window in (A): presence of little class information in the CSP features; (C) Control analysis: Group-level performance in classification of motor reaction presence for segments from the first and third tertile of individual RT distributions. Clear information presence in CSP components proves viability of the pipeline. Error bars denote SEM, asterisks denote the usual significance levels.

4 Discussion

Temporal dynamics of tactile perception

- All participants performed substantially above chance level, but sensitivity and specificity differed (descriptively) from person to person → apparent *between-subject* variability in ROCs
- Spill-over effect from previous trials: After a relatively slow reaction, participants are:
  - 19-35% likelier to make an incorrect intensity judgement
  - 9-22% likelier to perceive a weak stimulus

  → phasic *within-subject* variability in ROCs

Predictability of perceived intensity before stimulus onset

- Information about perceived intensity could only be linearly decoded using surrogate channel power in the **upper alpha band** for a *minority* of participants
- Limitations: No trial-wise prediction of SDT parameters possible; true intensity and previous-trial RT are confound variables → likely reason for small discriminability!

Outlook

- Dose-response curve for nuisance factors + cv-confound regression of previous trial *RT* [10]
- Or: Multi-class classification for each combination of *TI* and *PI* using a neural network
- Fit CSP filters using whole-trial information to increase their reliability
- Multi-band spatial filtering: use weighted channel power for multiple narrow-bands
- Tensor decomposition instead of CSP & LDA → increase performance and include interactions between spatial, temporal and spectral features (at the cost of interpretability)

Refs. [1] Busch et al. (2009), *J. Neurosci.*; [2] Linkenkaer-Hansen et al. (2004), *J. Neurosci.*; [3] Iemi et al. (2017), *J. Neurosci.*; [4] Craddock et al. (2017), *Neuropsychologia*; [5] Kloosterman et al. (2019), *eLife*; [6] Stephani et al. (in review), preprint in *biorXive*; [7] Blankertz et al. (2016), *Front. Neurosci.*; [8] Blankertz et al. (2008), *IEEE Signal Process. Mag.*; [9] Allefeld et al. (2016), *NeuroImage*; [10] Snoek et al. (2016), *NeuroImage*

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