Better Codes for the P300 Visual Speller

F. Bießmann, N.J. Hill, J. Farquhar, B. Schölkopf

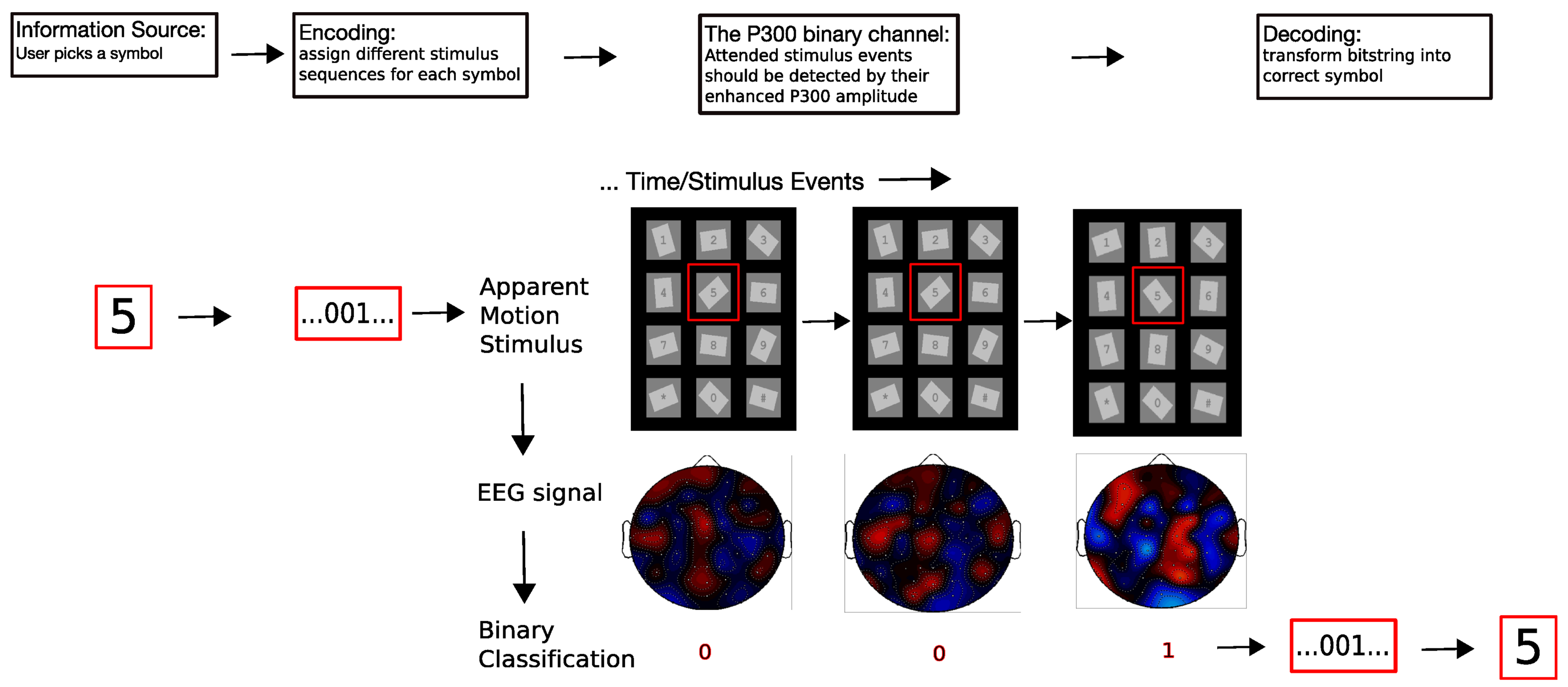
Max-Planck Institute for Biologial Cybernetics, Dept. Empirical Inference, Tübingen, Germany

MAX-PLANCK-GESELLSCHAFT

BIOLOGISCHE KYBERNETIK

Introduction

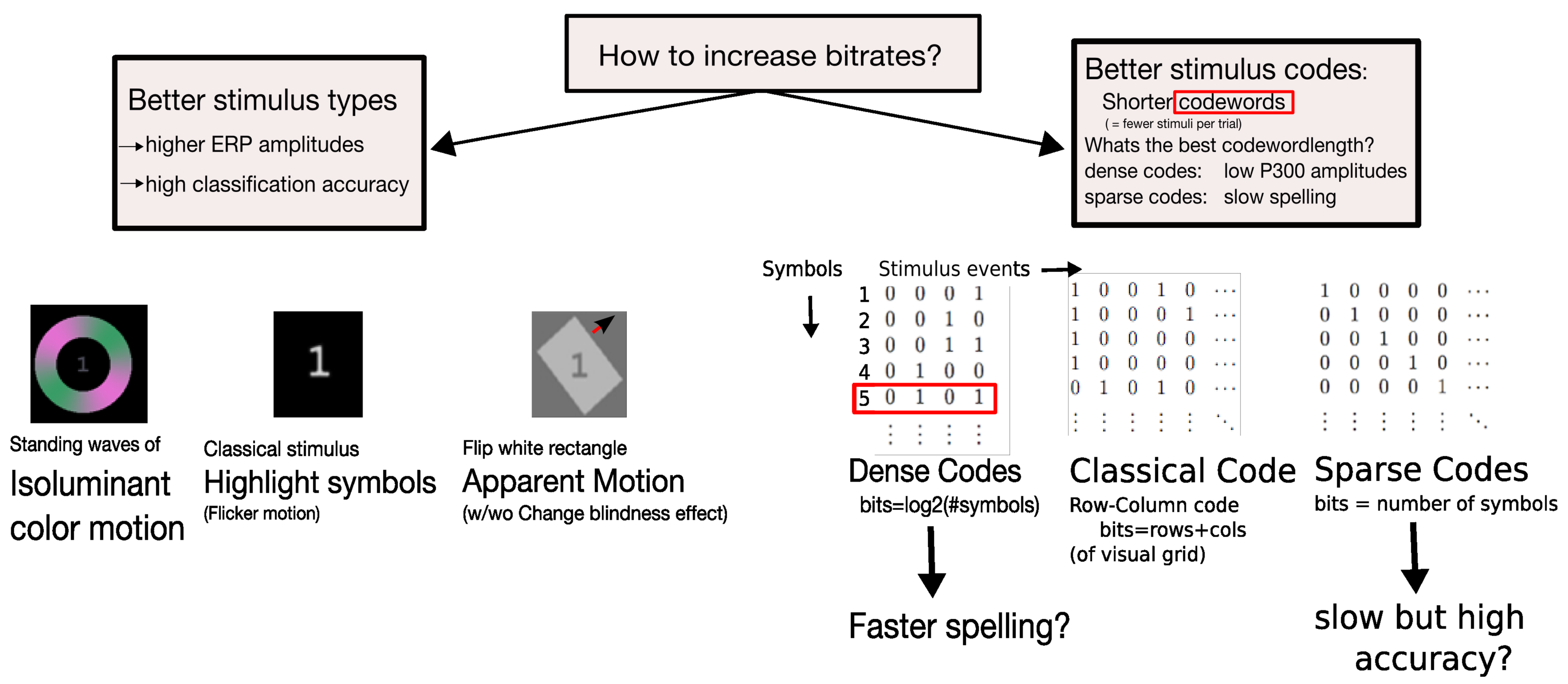
- **Brain-Computer interfaces (BCIs) could enable people suffering from amyotrophic lateral sclerosis (ALS) to communicate via brain activity [8].**
- **The P300 visual speller was first proposed by Farewell and Donchin [2] and has been shown to yield significantly higher bitrates than other BCI paradigms [5].**



We tried to improve the P300 visual speller bitrate using:

1. **Variations of classical stimulus types and codes**
2. **Error correcting codes**

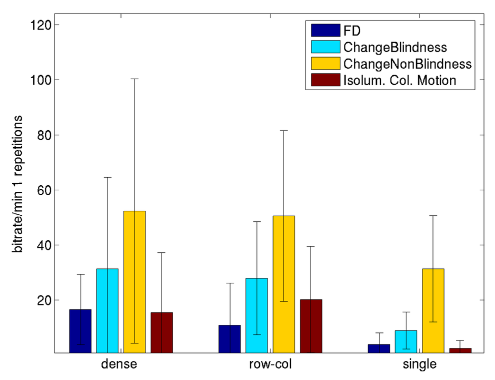
1 Effect of stimulus type and code on bitrate

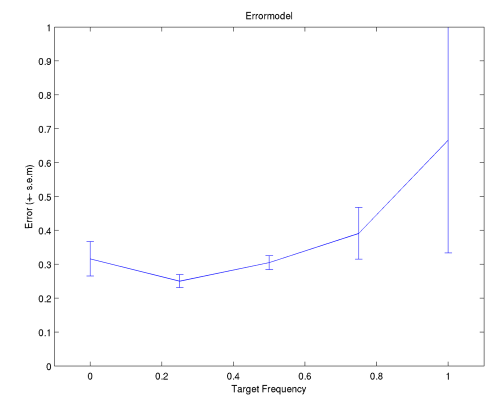


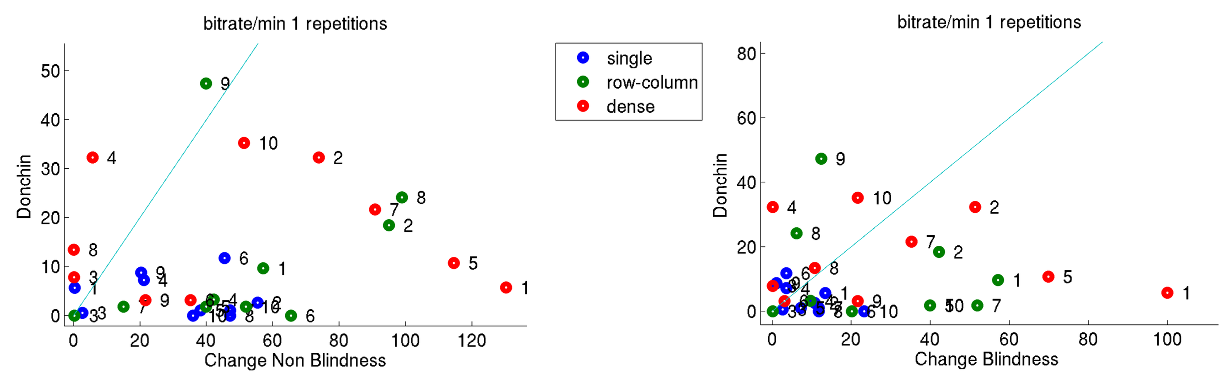
- 12-symbol visual grid (telephone keypad)
- 4 stimulus types:
  classical FD-type [2], Change(Non)Blindness [6], isoluminant colour motion [7]
- 3 stimulus codes of different density (=target frequency):
  dense code (12-by-4, mean density 50%), row-column code (12-by-7, mean density 16%), single code (12-by-12, mean density 8%)

Results Experiment 1

- **Dense codes can achieve higher bitrates than row-column codes (>100 bits/min).**
- **Error model shows: Single P300 epoch classification accuracy was similar for target frequencies of 0-2Hz with a slight tendency for more errors at high frequencies.**
- **Variations from classical stimulus yielded high bitrates: Apparent luminance contrast motion outperformed flicker motion consistently.**
- **Isoluminant color motion induced high P300 amplitudes, but low bitrates, due to slow stimulus.**







2 Error Correcting Codes

- 36-symbol grid
- Stimulus type: apparent motion
- Stimulus codes:
  36-by-12 RC code, 36-by-12 error correcting code, minimum hamming distance (D_H) 4 (1 error correction)
- 6 subjects copy-spelled *'Die Sonne ist von Kupfer'*.
- Decoding with help of prior on letters:
  trigram probabilities of german language were computed on training corpus from [1]
- Letter predictions maximized posterior probability of brain signal:

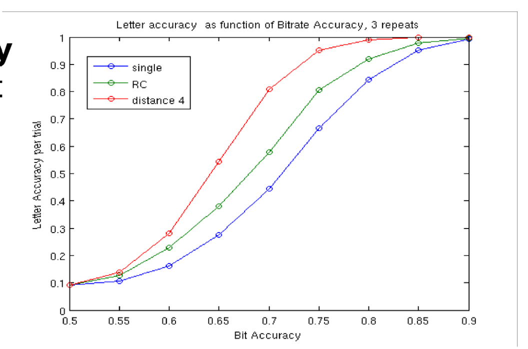
$$P(Letter_i|EEG) \propto P(EEG|Letter_i) \cdot P(Letter_i)$$

$$\begin{array}{ccccc} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \end{array}$$

Example of an Error correcting code: 3 words, length 5 bit, t = 1; if only one error occurs, words can still be uniquely identified because:

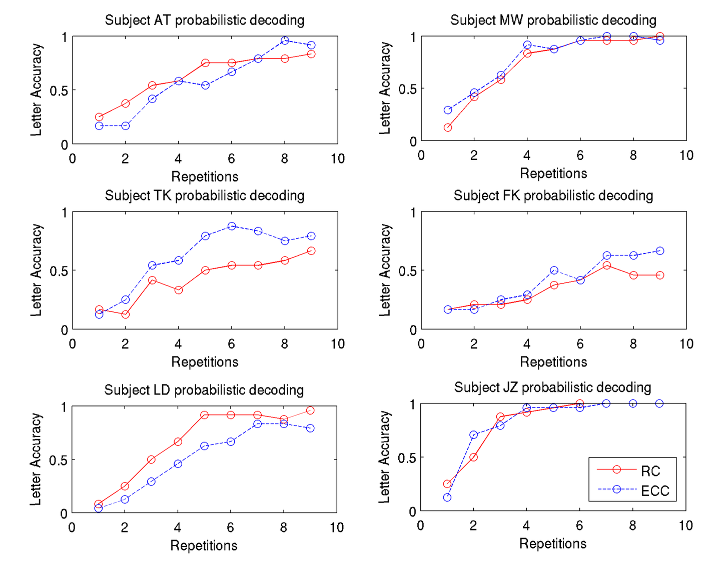
$$\sum_{i=1} \sum_{j=1} D_H(w_i, w_j) > 2t + 1$$

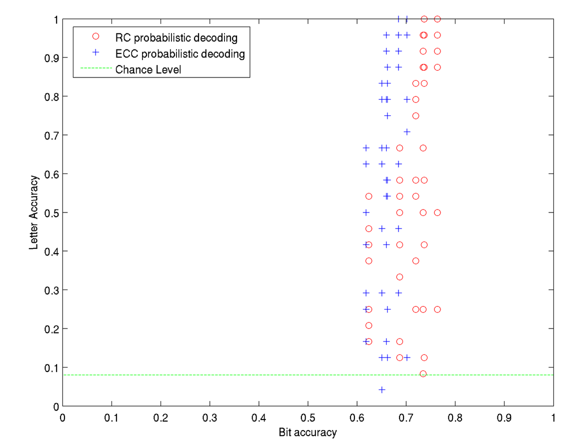
Letter accuracy as function of bit accuracy using different codes



Results Experiment 2

- **No difference between RC and ECC w.r.t letter accuracies.**
- **Letter accuracy as function of bit accuracy shows: ECC can compensate for low bit accuracy.**





3 Discussion

- Dense codes can outperform sparse codes (bitrates >100 bits/min).
- Variations from the classical stimulus type help to increase ERP amplitudes.
- High target frequencies (>4Hz) of ECCs decrease bit accuracy.
- ECCs still yield high letter accuracies.
- ECCs with same bit accuracies as RC codes will have higher accuracy with fewer trials.
- This has implications on any non-binary BCI or design of neuroimaging experiments.

Sensible stimulus sequences in form of error correcting codes could compensate for the noisyness of any neuroimaging technique and thus maximize the mutual information between experimental conditions and brainstates

Methods EEG data was recorded using the *ElectroCap128* (Electro-Cap International, Inc.) connected to a *QuickAmp* amplifier by *BrainVision*. We used only a subset (76) of the available 128 electrodes. Impedances were kept below $5K\Omega$. One electrode was used to record electro-oculograms. The data was bandpassed (0.1-30Hz) and downsampled accordingly. For classification, trials were split in windows of 0-600 ms after stimulus event onset. Before, the activity in all electrodes was decorrelated by a whitening transform. For classification we used kernel logistic regression (for probabilistic classification) and support-vector machines. Bitrates were computed using the definition of [9]: $BR = \frac{60}{t}(log_2 s + p_c log_2 p_c + (1-p_c) log_2 \frac{(1-p_c)}{(s-1)})$, where p_c =probability of correct letter, s=number of symbols, t=time (seconds) needed to spell one symbol.

References

[1] http://www.inference.phy.cam.ac.uk/dasher/.

[2] LA Farwell and E Donchin. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr Clin Neurophysiol*, 70(6):510–23, 1988.

[3] C Guan, M Thulasidas, and W Jiankang. High performance p300 speller for brain-computer interface. *Biomedical Circuits and Systems, 2004 IEEE International Workshop on*, 2004.

[4] BH Jansen, A Allam, P Kota, K Lachance, A Osho, and K Sundaresan. An exploratory study of factors affecting single trial p300 detection. *IEEE Trans Biomed Eng*, 51(6):975–8, 2004.

[5] M Kaper. P300-based computer interfacing. *PhD thesis*, 2006.

[6] RA Rensink. Change detection. *Annu Rev Psychol*, 53((null)):245–77, 2002.

[7] AE Seiffert and P Cavanagh. Position displacement, not velocity, is the cue to motion detection of second-order stimuli. *Vision Res*, 38(22):3569–82, 1998.

[8] EW Sellers and E Donchin. A p300-based brain-computer interface: initial tests by als patients. *Clin Neurophysiol*, 117(3):538–48, 2006.

[9] JR Wolpaw, N Birbaumer, DJ McFarland, G Pfurtscheller, and TM Vaughan. Brain-computer interfaces for communication and control. *Clin Neurophysiol*, 113(6):767–91, 2002.