A comparison of stimulus sequences for c-VEP based BCI

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INTRODUCTION

Problem Setting

A code-modulated visual evoked potential (c-VEP) is evoked activity observed in the EEG in response to rapid visual stimulation with a pseudo-random sequence of flashes [1]. Typically, sequences from telecommunication are used like an m-sequence or Gold codes [1].

Challenge

These sequences are optimized in the digital stimulus domain instead of in the EEG response domain, and carry-over between these domains is not a given. There is no good understanding of which stimulus sequence leads to optimal BCI performance.

Approach

Recently, several candidate stimuli were evaluated using **simulated EEG** showing that Golay and de Bruijn sequences outperform m-sequences and Gold codes [2]. In this study, we extend these simulation findings with an analysis on **recorded EEG** from 26 human participants.

METHODS

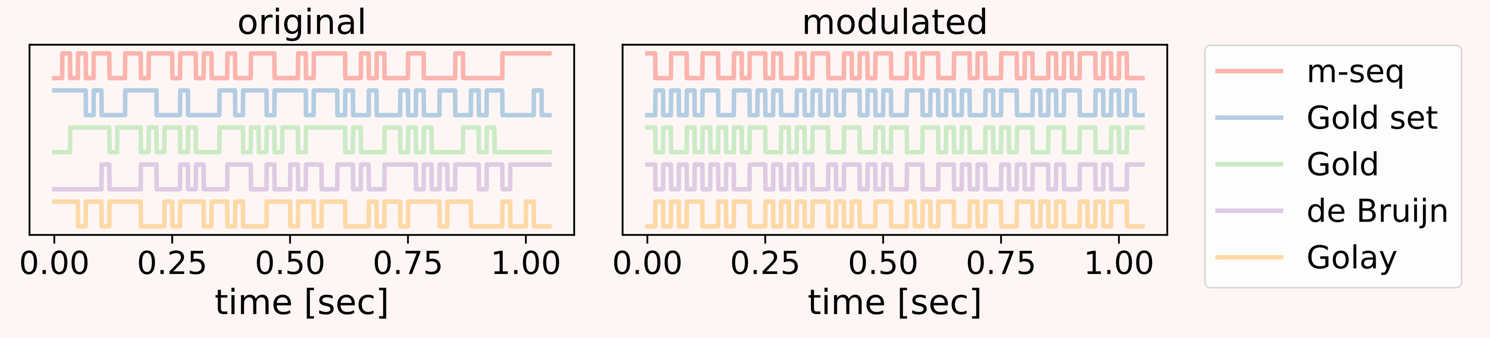
EEG acquisition

We recorded 64-channel EEG data at 2 kHz, which were band-pass filtered between 1 and 30 Hz, and downsampled to 240 Hz. For each of the 26 participants and each of the 10 stimulus sequences, 32 single-trials of 4.2 seconds were collected.

Stimulus presentation

Participants were shown a 4x8 matrix speller, in which each of the 32 symbols was luminance-modulated by one of 10 binary sequences. These sequences were (1) a shifted m-sequence, (2) a shifted Gold code, (3) a set of Gold codes, (4) a shifted de Bruijn sequence, and (5) a shifted Golay sequence. Each sequence was presented as original or as modulated via XOR with a double-frequency bit-clock to limit low-frequency content [3].

Sequences



Decoding with rCCA

For each of the stimulus sequences, a 4-fold cross-validation was performed. The decoder was a template-matching classifier using reconvolution [4]:

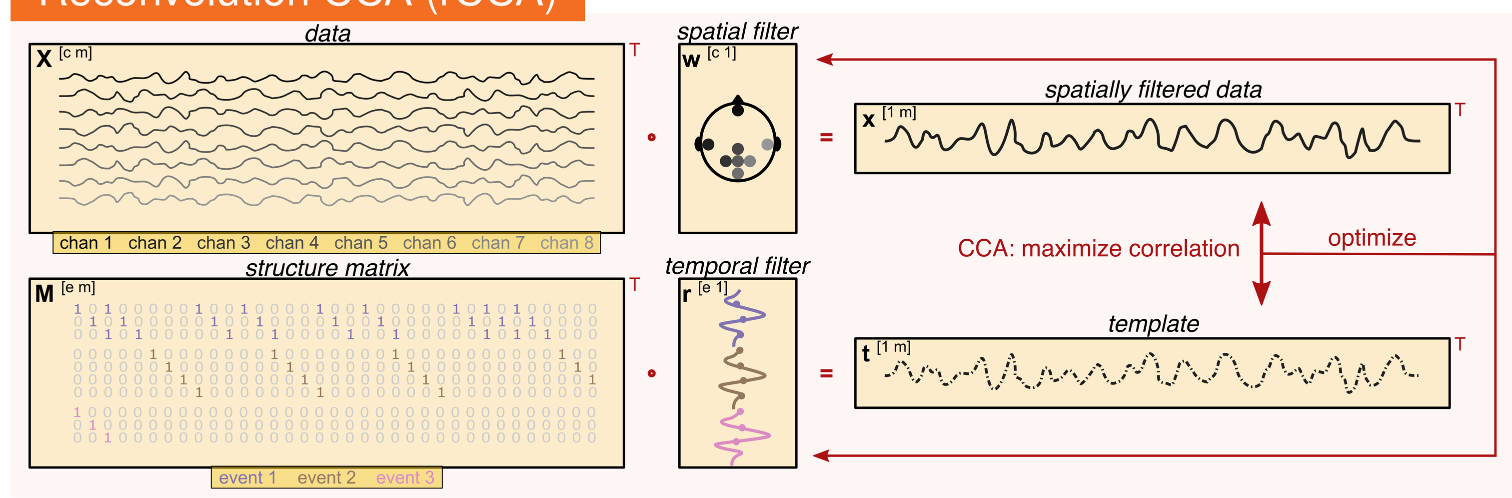
$$\hat{y} = \arg\max_i \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{r}^\top \mathbf{M}_i)$$

with the single-trial $\mathbf{X} \in \mathbb{R}^{c \times m}$ for c channels and m samples, the spatial filter $\mathbf{w} \in \mathbb{R}^c$, the design matrix $\mathbf{M}_i \in \mathbb{R}^{e \times m}$ of the ith class for e event samples, and the temporal filter $\mathbf{r} \in \mathbb{R}^n$. This decoder's parameters were calculated with canonical correlation analysis (CCA):

$$\max_{\mathbf{w},\mathbf{r}} \rho(\mathbf{w}^\top \tilde{\mathbf{X}}, \mathbf{r}^\top \tilde{\mathbf{M}})$$

with stacked EEG $\tilde{\mathbf{X}} \in \mathbb{R}^{c \times m \cdot k}$ for k training trials and stacked design matrices $\tilde{\mathbf{M}} \in \mathbb{R}^{e \times m \cdot k}$.

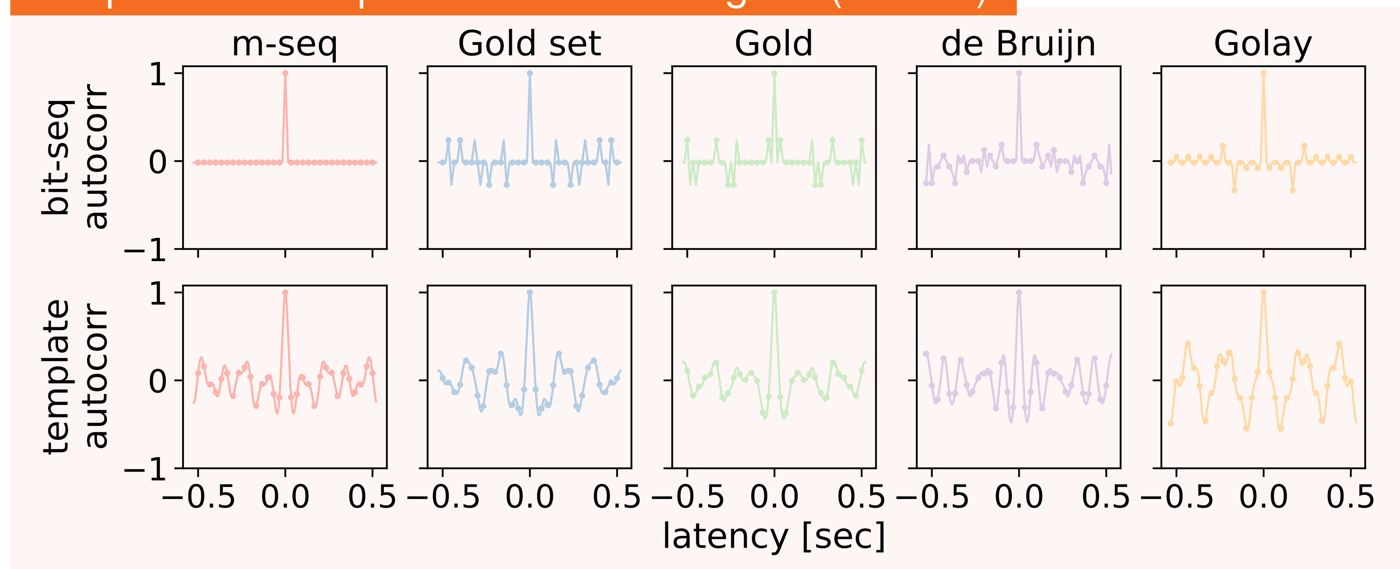
Reconvolution CCA (rCCA)



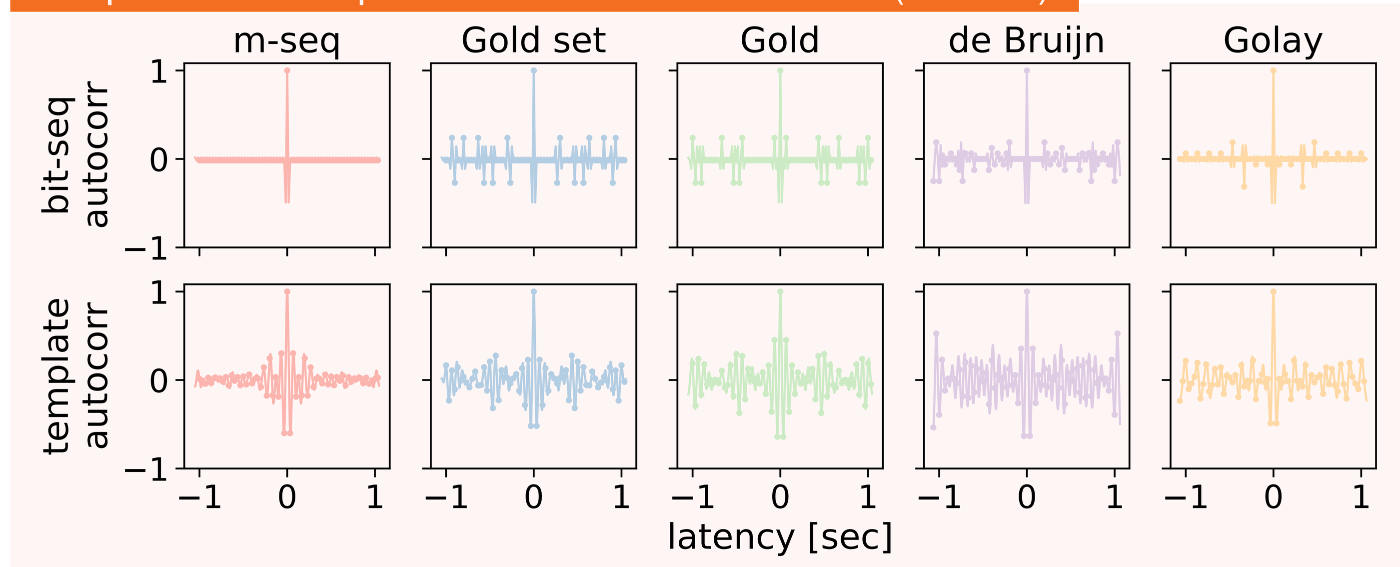
RESULTS

CORRELATION ANALYSIS

Sequence & template correlation original (sub-01)

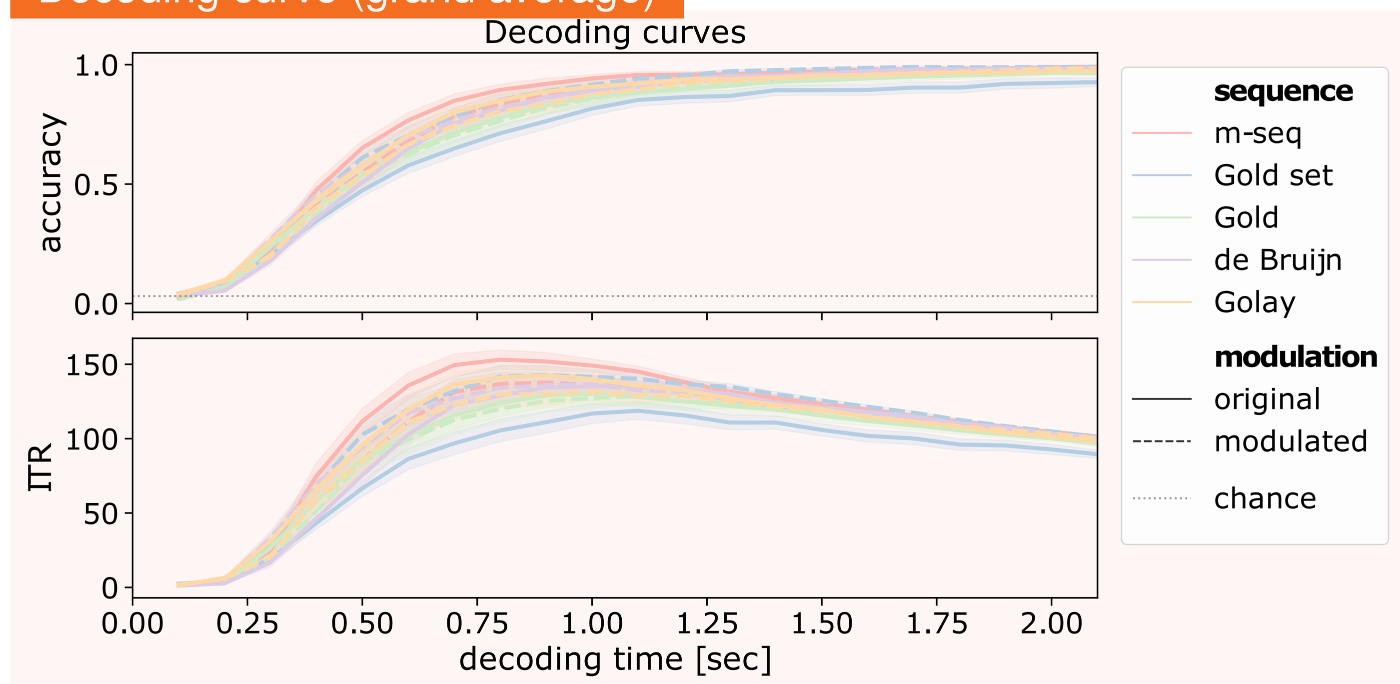


Sequence & template correlation modulated (sub-01)



DECODING ANALYSIS

Decoding curve (grand average)



Decoding performance (grand average)

	original					modulated				
Seq.	m-seq	Gold set	Gold	de Bruijn	Golay	m-seq	Gold set	Gold	de Bruijn	Golay
P	0.89	0.85	0.86	0.89	0.89	0.87	0.89	0.89	0.89	0.88
T	0.80	1.10	1.00	1.00	0.90	0.90	0.90	1.10	1.00	1.00
ITR	**153.1**	118.8	130.1	135.2	142.2	137.2	**142.8**	128.6	136.4	131.8

Statistics

According to a one-sided paired Wilcoxon signed-rank test (N=26):

- Original > modulated: $p = .926$ ($\delta = -4.2$)
- Original m-seq > original Golay: $p = .020$ ($\delta = 9.5$)
- Modulated Gold set > modulated m-seq: $p = .006$ ($\delta = 8.3$)
- Individual best > original m-seq: $p < 0.001$ ($\delta = 13.5$)

DISCUSSION

Correlation properties do not translate from stimulus to response

As can be observed in the correlation analysis, the overall auto-correlation pattern in the response domain is substantially distorted as compared to the auto-correlation in the stimulus domain. This effect can be explained by the non-linear visual system, that can be characterized as the convolution of the stimulus sequence with a transient response [3-4]. This implies that stimulus **sequences used in a c-VEP BCI should not be optimized in the stimulus domain, but rather in the response domain**.

Original m-sequence is best over population

In this study, 10 different sequences were tested. On average, the original m-sequence performed best (153.1 bits/min.). However, despite the modulated Gold set performing less well (142.8 bits/min.), the overall difference between original and modulated codes was not significant. These results are in conflict with the simulation results that favored the Golay and de Bruijn sequence [2]. These empirical results imply that for a new user there are several good performing sequences available, of which **the m-sequence is likely to reach highest decoding performance**.

Individual best sequence substantially varies

As can be observed from the decoding analysis, there is substantial overlap between the performances as achieved by each of the sequences. Instead of optimizing a sequence for the entire population of users, one could also appreciate this variance and optimize the sequence per individual. This individually optimized performance was significantly higher than the average performance. The individually best sequences were the original m-sequence (7/26), modulated Gold code set (6/26), modulated de Bruijn sequence (4/26), modulated m-sequence (3/26), original Golay sequence (3/26), original Gold code (2/26), and modulated Golay sequence (1/26). This implies that one should not rely on a "standard" or "average" stimulus sequence, but instead **one should optimize the sequence with the user in the loop to achieve optimal performance**.

OPEN QUESTIONS

What are c-VEP's underlying neural mechanisms?

The model (rCCA [3-4]) used in this study assumes the linear superposition hypothesis [5]: the response to a sequence of events is the linear addition of the responses to the individual events. Knowing that the brain is non-linear (e.g., habituation), there is substantial room for improvement, for which a better understanding is needed of how sequences of flashes lead to the observed brain activity. This may also improve the quality of *simulated* data.

What are stimulus properties that define a good sequence?

So far, many studies have experimented with pre-defined sequences from telecommunication [1] or have started to manually optimize sequences (see e.g., [6]). Unfortunately, a good understanding of why certain sequences lead to higher performance is still lacking.

How to search for the optimal stimulus sequence?

In the BCI domain, it is relatively standard that (hyper)parameters of the BCI system, such as the experimental protocol (e.g., stimulus characteristics and timing) are optimized for the entire population. Instead, acknowledging the large subject-to-subject variance, one should optimize such (hyper)parameters *with the user in the loop* (see e.g., [7]). This poses new challenges of how to optimize this vast amount of parameters in real-time and limted training datasets (i.e., a short calibration session).

REFERENCES

[1] Martinez-Cagigal et al. (2021) *J Neural Eng* doi:10.1088/1741-2552/ac38cf

[2] Torres & Daly (2021) *J Neural Eng* doi:10.1088/1741-2552/ac38cf

[3] Thielen et al. (2015) *PLOS ONE* doi:10.1371/journal.pone.0133797

[4] Thielen et al. (2021) *J Neural Eng* doi:10.1088/1741-2552/abecef

[5] Capilla et al. (2011) *PLOS ONE* doi:10.1371/journal.pone.0014543

[6] Yasinzai & Ider (2020) *Biomed Phys & Eng Express* doi:10.1088/2057-1976/ab98e7

[7] Sosulski et al. (2021) *Archiv* doi:10.48550/arXiv.2109.06011

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