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Finding optimal stimulation patterns for BCIs based on visual evoked potentials

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Introduction – Issues in VEP BCI development

VEP generation

Most prominent parts of a VEP to a single stimulus lasts for approximately 250 ms post-stimulus. Successive stimuli within a lower time interval result in mixed VEPs and it is not entirely clear how this mix-up proceeds:

– Simple overlap of responses? [1,2]

– Does the brain entrain to the modulated stimuli? [3]

Modulation patterns

In order to get best classification performances it is required to find modulation patterns evoking brain responses which can be differentiated between others as effectively as possible.

Methods – Random VEP model

General model description

Instead of using a static modulation pattern for each target, fully random patterns are used. A ridge regression model is trained using each 250 ms window of spatially filtered EEG data as predictors and the current random bits as responses.
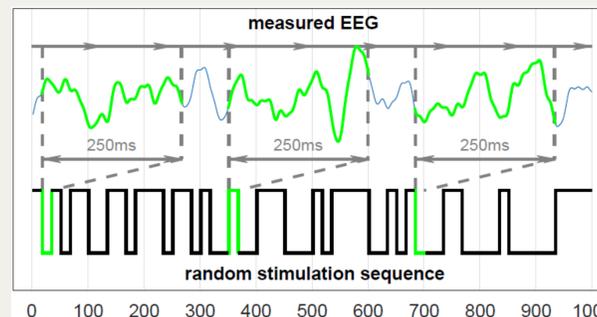

Figure 1: Training of the RVEP model. Each 250ms window of the spatially filtered EEG data will be projected to current bit (highlighted in green) of the corresponding random stimulation sequence.

Methods – Prediction

Bit prediction

Contrary to recent VEP BCIs predicting whole trials, our method predicts the modulation sequence continuously. For this, the regression model predicts a real number for each window of 250 ms of EEG data which in turn is transferred to a bit sequence by a threshold of 0.5.

Optimized modulation patterns

Using the data of our previous study [4] we analyzed the bit prediction accuracies of all 15 bit (250 ms @ 60 Hz) subsequences and found that the number of bit changes of those subsequences affects the bit prediction accuracy. To proof the findings, we generated a set of 15 bit long sequences with 7 bit changes (50% bit change probability), resulted in 6,864 bit sequences in total. Out of those we chose 150 sequences which were used for optimized modulation.
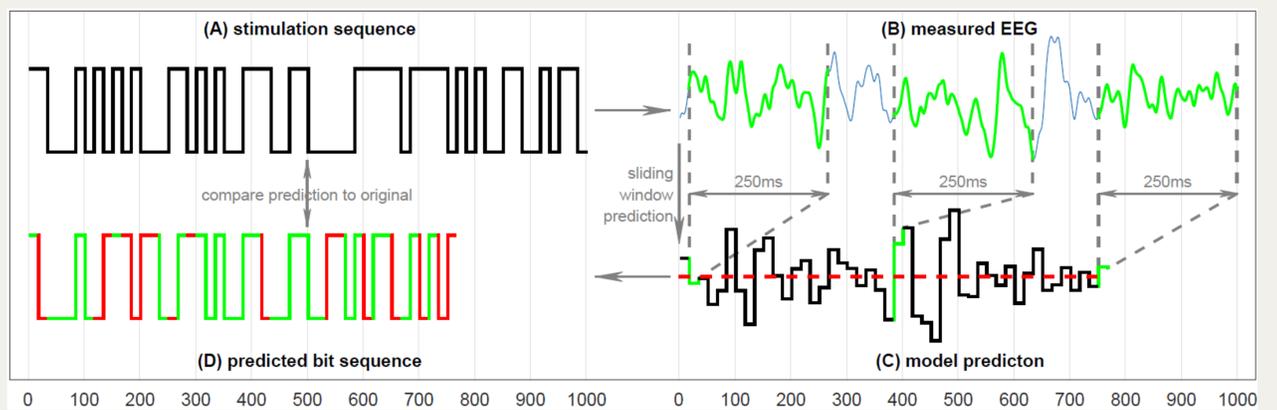

Figure 2: Schematic of the RVEP bit and target prediction. **A** Stimulation sequence. **B** 250ms windows (highlighted in green) are slid sample-wise over the spatially filtered EEG signal. **C** Regression model predicts a real number for window (again, highlighted in green). The red dashed line indicates the threshold of 0.5. **D** Each value above 0.5 is interpreted as 1, and 0 otherwise. Predicted bit sequence can be compared to the stimulation sequence (match = green, mismatch = red).

Results – Bit changes

Figure 3: Bit prediction accuracies of all 15 bit subsequences of the random modulated trials relative to the bit change probability (number of bit changes). Data from previous study [4], averaged results of 9 subjects.
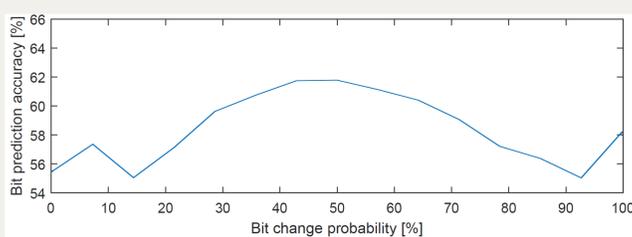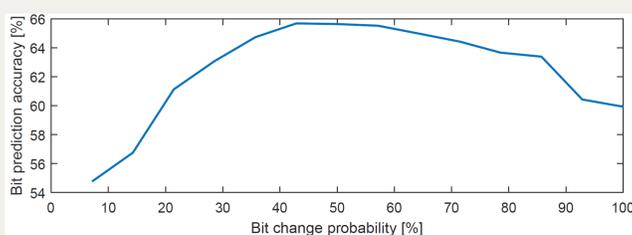

Figure 4: Bit prediction accuracies of all 15 bit subsequences of the random modulated trials relative to the bit change probability (number of bit changes). Data from current study, averaged results of 9 subjects.
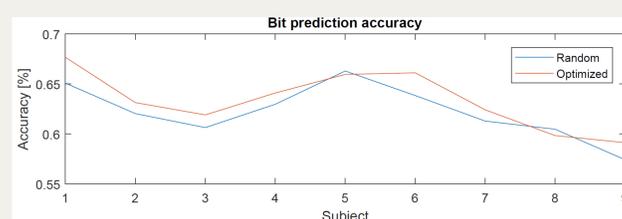
Results – Bit prediction

Figure 5: Bit predictions accuracies of 224 random modulated trials (blue lines) and 224 trials with optimized modulation patterns (red lines) of all 9 subjects.
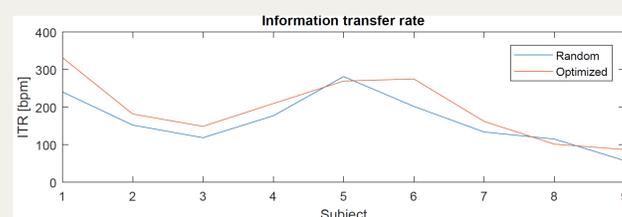

Figure 6: Information transfer rates (ITRs) of 224 random modulated trials (blue lines) and 224 trials with optimized modulation patterns (red lines) of all 9 subjects.

Summary and Discussion

– We introduced a new approach to optimize visual modulation patterns by using specific properties

– We proofed that the bit change probability (number of bit changes) plays a significant ($p < 0.05$, t-test) role for the prediction accuracy

– The optimal bit change probability amounts 50% which means an average of 7 bit changes in a 15 bit subsequence (at 60 Hz modulation rate).

– Using the optimized stimulation patterns the average ITR increased from 193.7 bpm to 251.7 bpm

– Our method allows to "search" for further properties of modulation patterns in order to optimize them even more

– The overall increased performance between previous and current data is due to some synchronization errors during the previous study

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