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RANDOM VISUAL EVOKED POTENTIALS (RVEP) FOR BRAIN-COMPUTER INTERFACE (BCI) CONTROL

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ABSTRACT: Brain-Computer Interfaces (BCIs) enable users to control devices or communicate by using brain activity only. While BCIs based on visual evoked potentials (VEPs) have been shown to achieve high performance, we present a different paradigm for BCI control: random VEP (rVEP). We designed a regression model, trained on VEPs of fully random bit codes. Afterwards, the model is able to perform a bit-wise prediction of a previously unseen stimulation sequence, which in turn can be used for BCI control. In an offline study, the model predicts unknown stimulation sequences with an average ITR of 94.5 bits per minute (bpm) and up to 281 bpm on a single-trial level. In a copy-spelling task, the model achieved an average ITR of 64.3 bpm and up to 115.5 bpm.

INTRODUCTION

Using a Brain-Computer Interface (BCI), a user is able to control a computer by brain activity without physical activity. In general, BCIs are used to restore functionalities of handicapped people, like restoring communication ability of people who are not able to communicate by muscle activity. The EEG of the brain's response to a visual stimulus, called visual evoked potential (VEP), is one commonly used method for BCI control.

For rare stimuli (less than 2 Hz) the VEP includes three major early components: C1 (60-80 ms), P1 (80-120 ms), and N1 (120–180 ms) [1]. If stimuli become more rapid, the single VEPs can no longer be determined. How the brain responds to overlapping stimuli is not entirely clear, as it could be a simple overlap of the VEPs or the brain is entrained to the stimulus frequency [2].

One of the earliest papers proposing the use of VEPs for BCI control was published by Sutter in 1984 [3]. To date, several types of stimuli were tested for BCI control, most commonly steady state VEPs (SSVEPs) or code-modulated VEPs (cVEPs). SSVEP BCIs make use of frequency modulated stimuli, and the brain's response can be interpreted, for example, by using the frequency domain. For cVEP BCIs, the stimuli are code modulated, i.e. a pseudorandom code with a low auto-correlation which is shifted for the different targets. The fastest SSVEP BCI has an information transfer rate (ITR) of 319 bits per minute (bpm) [4], whereas the fastest cVEP BCI achieves an ITR of 144 bpm [5].

Current BCIs based on VEPs have been shown to achieve high performance, but all methods are not able to interpret VEPs of arbitrary stimuli. The only study, known to us, researching VEPs of arbitrary stimuli is by Thielen *et al.* [6]. They developed a convolution model, making the assumption that the composition of VEPs induced by the parts of a decomposed modulation sequence should yield the same result as the VEP pattern induced by the modulated sequence. For this, the model was trained to predict the "single" VEPs of a decomposed modulation sequence, which in turn are composed to the predicted chain of VEPs. For an unseen modulation sequence the predicted chain of VEPs is then compared to the real measured brain's answer, in order to select one of the $6 \times 6 = 36$ targets. But the modulation sequences are not fully random, as they are composed of short and long pulses.

In this paper, we present a method to predict the bit-sequence of a fully randomly modulated stimulus and demonstrate how this can be used for BCI control based on random visual evoked potentials (rVEP).

MATERIALS AND METHODS

The rVEP BCI is based on a simple regression model, which is able to interpret the EEG signal during an arbitrary stimulation. The model uses a bit-wise prediction of the modulation sequence, which in turn can be applied for BCI control.

Bit-wise prediction: Yet, it is unclear how the VEPs are generated by the brain if the duration of two successive stimuli is lower than the duration of a single VEP (approx. 250 ms). We propose a new paradigm where sliding windows of 250 ms of the EEG data are used to predict the modulation sequence. After training, the regression model is able to predict an arbitrary and previously unseen modulation sequence by sliding the window sample-wise. A schematic representation of the rVEP prediction is illustrated in Fig. 1. For each 250 ms window of the EEG signal, the regression model predicts a real number. In order to get a bit-sequence, we defined that each predicted value above 0.5 is a boolean 1, and 0 otherwise. To get the prediction accuracy, we use the hamming distance between the predicted bit sequence and the stimulation bit sequence. Because the distances are 1's and 0's, the averaged distance of all samples corresponds to the accuracy of how much of the stimulation sequence can be predicted correctly. In short, we do an ongoing prediction of the

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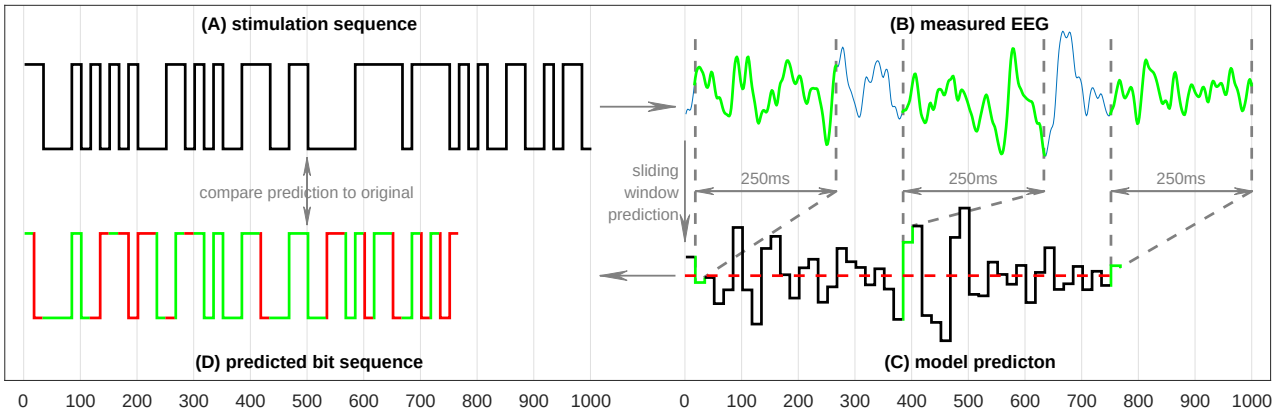

Figure 1: Schematic of the rVEP prediction. **A** Once the model is trained, an unseen (random) stimulation sequence can be used for prediction. **B** A 250ms window (highlighted in green) will be slided sample-wise over the spatially filtered EEG signal. For simplicity, it is shown bit-wise using 3 exemplary windows. **C** The trained model predicts a real number for each 250ms window (again, highlighted in green). The red dashed line indicates a value of 0.5. **D** Each value above 0.5 is interpreted as boolean 1, and as 0 otherwise. The resulting bit sequence can be compared to the stimulation sequence (match = green, mismatch = red).

modulation sequence using the following 250 ms of the EEG data after the stimulus.

BCI control: For BCI control, we need a method to choose the correct target out of others. For this, we used two methods: (1) The most obvious method is to compare the predicted bit sequence to modulation sequences of all possible targets, the one with the highest accuracy will be chosen. But the bit-wise prediction does not allow differentiation between how large (or small) the predicted real number really is, this approach wastes additional information. (2) To address this, we used a ”distance” prediction of each target. We calculated euclidean distances of predicted real numbers to the corresponding target bits and the one with the shortest distance will be chosen.

BCI design: The rVEP BCI consists of an EEG amplifier, a personal computer (PC) and a CRT Monitor, because of its near-to-zero reaction time and the resulting sharp transitions between black and white. The presentation of the stimuli are operated from the PC and synchronized with the EEG amplifier by using the parallel port. BCI2000 [7] is used as a general framework for recording the data. The visual stimuli are presented on a 17 inch CRT Monitor with a 60 Hz refresh rate and a resolution of 1280×1024 pixel. The subjects are seated approximately 80 cm in front of the monitor. To ensure synchronization of the presented stimuli with the refresh rate of the CRT monitor, DirectX (Microsoft Inc.) is used for programming the stimulation module.

A stimulus can either be black or white, which can be represented by 0 or 1 in a binary sequence. Each stimulus was modulated with a random binary sequence using a 60 Hz refresh rate. The rVEP BCI consists of 32 targets (i.e. stimuli) which are arranged as a 4×8 matrix and surrounded by 28 complementary non-target stimuli. The targets were used to select one of the 26 letters from the alphabet as well as underscore and numbers 1 to 5. A screenshot of the layout that was displayed to the subjects can be seen in Fig. 2.

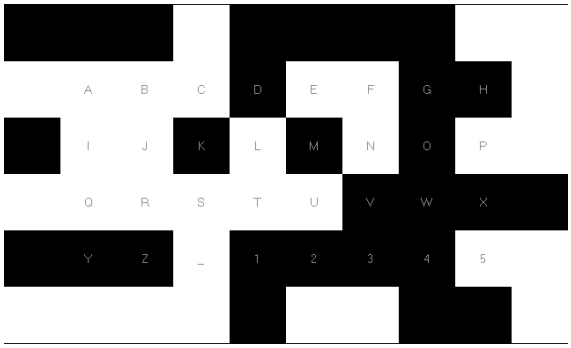

Figure 2: Screenshot of the rVEP BCI during a trial showing the target layout and non-targets.

EEG data was recorded with a g.tec g.USBamp at a samplingrate of 600 Hz and a Brainproducts Acticap system with 32 channels. Locations of the 29 EEG electrodes are depicted in Fig. 3. The ground electrode was positioned at AFz and the reference electrode at FCz. Three electrooculogram (EOG) electrodes were placed beside the left eye, right eye and at the center above the eyes. The data was notch-filtered by the amplifier at 50 Hz.

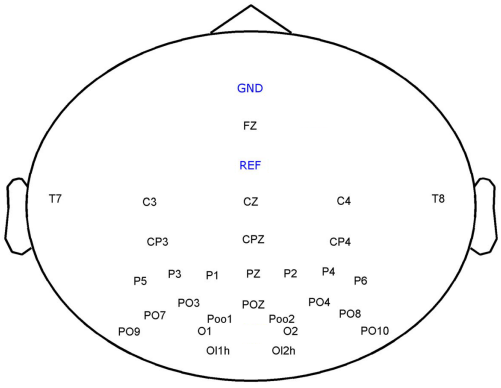

Figure 3: Location of the 29 EEG electrodes. Ground electrode (GND) was positioned at AFz and reference electrode (REF) at FCz.

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A spatial filter is applied to the EEG data using the Canonical Correlation Analysis (CCA) as described by Spüler *et al.* [8]. First, one needs to find the best EEG channel where the cVEP is most prominent. The EEG data of this channel is averaged over all cVEP sequence cycles and used to calculate the spatial filter. For this, each subject has to perform some cVEP trials. The spatially filtered EEG signal is used as input for the regression model.
During the training we use fully random stimulation sequences and do a regression on each 250 ms window (shifted sample-wisely) of the spatially filtered EEG data to its corresponding bit modulated at the time the window starts (see Fig. 4). We make the assumption that a fully random stimulation should be sufficient to cover most possibilities of different stimulation patterns within a window of 250 ms, provided that the random sequence is long enough. Afterwards the coefficients obtained by the regression model are used for prediction.

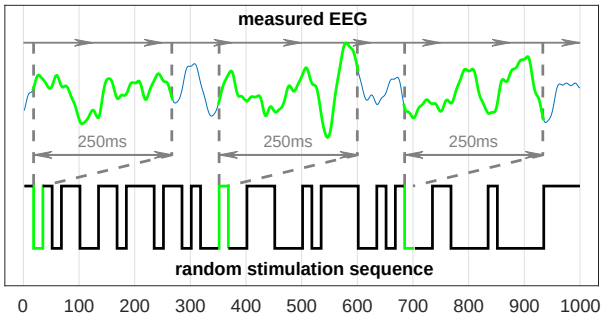

Figure 4: Training of the rVEP model. Each 250ms window of the spatially filtered EEG data will be projected to its correspondig bit (1 or 0, highlighted in green) of the corresponding random stimulation sequence.

Experiment design: To test the system, 9 healthy subjects, named S1 to S9, were recruited. All subjects had normal or corrected-to-normal vision. A summary over age, sex and vision of the subjects can be found in Tab. 1. Each subject participated in one session and completed the whole experiment. None of the subjects ever participated in another VEP EEG study.

Table 1: Subject overview. Sex and age of the subjects and if they are wearing glasses.

Subject:	S1	S2	S3	S4	S5	S6	S7	S8	S9
Sex:	w	m	m	w	w	w	w	m	m
Age:	21	19	17	18	20	19	20	22	19
Glasses:	√	×	×	×	×	√	√	×	×

The experiment was structured in three phases consisting of 16 runs in total. The first 3 runs were used for the spatial filter, the following 3 runs are the training phase of the BCI and the remaining 10 runs form the testing phase. At each run the subjects had to perform a copy-spelling task where they had to look once at each of the 32 targets in lexicographic order (A-Z, underscore, 1-5). The duration of the 32 trials was constant within each run of a phase, but varies between the three phases. At the end of a trial a target was selected, meaning that the corresponding box was highlighted in yellow for 100 ms while the rest of the matrix was darkened for the same time, to guide the subject through the experiment. During the time between the trials, called pause, the flickering continued, but the recorded EEG data was not used for training or classification. The pause between the runs amounted approximately 30 to 60 seconds.

Spatial filter phase: A cVEP modulation was used during the spatial filter phase, because random modulation is unsuitable to train a spatial filter since the EEG data has to be averaged over a static modulation in order to filter the noise. The cVEP setup was equal to the system of Spüler *et al.* [5]. For modulation of the targets we used a 63-bit binary m-sequence, because of its low auto-correlation property [9]. For each target the same m-sequence was used for modulation, but shifted circularly by 2 bits for each successive target. During each trial, the stimulation sequence was repeated 3 times. Because the length of the stimulation sequence is $63\ bit/60\ {}^{bit}/_{s} = 1.05s$, the duration of a trial is $3 \cdot 1.05s = 3.15s$. One stimulation sequence is presented during the inter-trial-pause, therefore, the subject had $1.05s$ to move on an fixate the next target. In total, the spatial filter phase consists of $3 \cdot 32 \cdot 3 = 288$ presented m-sequences, excluding the pauses.

Training phase: During the 3 runs of the training phase, each trial had a length of 5 seconds in which 300 random bits were presented. The inter-trial-pause had a length of 2 seconds during which the subject had to look at the subsequent target. Since the layout has 32 targets, the subjects have to pass 96 trials. Each trial was spatially filtered, resulting in vectors of 3000 samples (10 samples per bit). Each vector was split into windows of 150 samples (= 250 ms), shifted by 1 sample. Since the last 150 windows do not have 150 successive samples, they are excluded from the data. The resulting matrix is of size 2850×150. The vector of the corresponding random modulation sequence has also a length of 2850 samples (last 150 samples are excluded, too). The matrix and the random modulation sequence vector are used as input (predictors and observed responses, respectively) of the ridge regression model (see Fig. 4). Since the method is a proof-of-concept, we did not optimize the regression parameter λ, but it was set to its default value 1. The output of the trained model are 151 coefficients, one for each input sample and a constant term.

Testing phase: The 10 runs of the testing phase are similar to the ones of the training phase, except that a trial had a length of 2 seconds instead of 5 seconds, resulting in 320 trials (32 per run). Each test trial was spatially-filtered and split into windows of 150 samples, same procedure as for the training trials, resulting in a matrix of size 1050×150 (last 150 windows were skipped). Afterwards, the matrix was applied to the trained regression model (multiplied with the coefficients), resulting in a vector of 1050 samples, this is called the model prediction.
In order to use the model prediction p for BCI control,

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we used two different methods: (1) Interpret each model prediction value above 0.5 as a binary 1 and 0 otherwise. The result is a predicted binary vector b which can be compared to the binary modulation sequences s_i of all targets i. For this we used the hamming distance h_i between b and each possible s_i. The target i with the lowest h_i was selected. (2) The second method is to calculate the euclidean distance e_i between p and s_i for each target i. The target i with minimum e_i is selected.

Random bit generation: During both the training and testing phase the MT19937 [10] random generator was used for modulation of the 60 boxes. At each monitor refresh a random integer (0 or 1) is generated for each of the 60 boxes (targets and non-targets), therefore, each box's binary sequence is always random without conscious repetitions and generated with a rate of 60 bits per second, continuously. The "order" of the generated bits can be varied by an assignable random seed.

Performance Evaluation: To compare the results for the different subjects and for the different modulation types (rVEP and cVEP), the accuracy of both the model prediction and the target classifier as well as the corresponding information transfer rate (ITR) [11] were used. The ITR can be computed with the following equation:

$$ITR = \log_2 N + P \log_2 P + (1-P) \log_2 \frac{1-P}{N-1}$$

with N the number of classes and P the accuracy.

RESULTS

Although a cross-validation could be used, such a simulated online design takes into account non-stationarity effects over time that can also occur in online experiments. As such non-stationary effects don't play a role in an evaluation using a cross-validation, the evaluation used is closer to the realistic online BCI.

Bit sequence prediction: To analyze the performance of the bit sequence prediction, all 320 predicted test sequences of each subject were compared to their modulated random bit sequence. For this, the accuracies of correctly predicted bits were calculated. The results are shown in Tab. 2. On average, the regression model achieves a performance of 59.1% over all subjects, meaning that 59.1% of all $302{,}400$ bits were predicted correctly, which corresponds to an average ITR of 94.5 bits per minute (bpm). It should be noted that subject S9 achieves an average performance of 63.7%, which implies an average ITR of 197.2 bpm.

Target prediction using hamming distance: In order to use the method for an online BCI, it is required to identify the correct target. For this, we calculated the hamming distances between all possible target sequences and the predicted sequence. The one with the minimal hamming distance was chosen. Averaged over all runs and all subjects, 60.6% of all targets were predicted correctly, this is an ITR of 44.8 bpm, including the inter-trial time of 1s. Subjects S8 and S9 achieved an average performance of >90% (ITR >83 bpm). A comparison of the target prediction and the bit prediction is shown in Tab. 2. Excluding the inter-trial time, the ITR of the target prediction is 27.2 bpm lower compared to the bit prediction.

Table 2: Comparison of the bit prediction and target prediction using the hamming distance. Accuracies (P) are given in percentages of correctly predicted bits and percentages of correct classifications of the 32 targets, respectively. 60 bits are presented per second, whereas the trial duration of the target prediction amounts 2s. The Information Transfer Rates (ITR) are estimated excluding the inter-trial time.

	target prediction		**bit prediction**	
	P (%)	ITR (bpm)	P (%)	ITR (bpm)
S1	28.1	17.5	54.8	24.3
S2	78.4	95.4	60.6	116.7
S3	47.8	42.5	57.2	55.3
S4	91.6	124.9	62.9	174.5
S5	53.1	50.4	58.2	70.6
S6	52.2	49.0	58.3	72.5
S7	69.1	77.2	60.0	104.0
S8	33.1	23.1	55.9	35.6
S9	91.9	125.1	63.7	197.2
∅	60.6	67.3	59.1	94.5

Target prediction using euclidean distance: The results of the correctly predicted targets within each run of all subjects are shown in Tab. 3. Using this method, on average 66.9% of all targets were predicted correctly. This implies an average ITR of 52.6 bpm (including the inter-trial time of 1s). It is worth to note that subject S9 achieves 100% in 4 of the 10 runs with an minimum accuracy of 93.8% and an average ITR of 94.8 bpm. Excluding the inter-trial time, the ITR of the target prediction is 15.6 bpm lower compared to the bit prediction.

Table 3: Performance of each subject using the "distance" method for target prediction. Accuracies (P) are given in percentages of correct classifications of the rVEP test runs and the cVEP runs, respectively. The trial duration (T) differs for rVEP and cVEP runs. The Information Transfer Rates (ITR) are estimated including the inter-trial time of 1s.

	rVEP			**cVEP**		
	P (%)	T (sec)	ITR (bpm)	P (%)	T (sec)	ITR (bpm)
S1	31.9	2	14.4	39.2	1.05	30.0
S2	87.8	2	77.2	75.3	1.05	87.0
S3	51.6	2	32.0	53.1	1.05	49.2
S4	93.1	2	86.0	88.9	1.05	115.5
S5	59.7	2	40.6	55.2	1.05	52.4
S6	65.6	2	47.4	63.5	1.05	65.8
S7	76.9	2	61.5	47.6	1.05	41.1
S8	37.8	2	19.2	33.7	1.05	23.2
S9	97.8	2	94.8	88.5	1.05	114.7
∅	66.9	2	52.6	60.6	1.05	64.3

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Comparison to cVEP sequence prediction: In order to compare the rVEP BCI with other VEP BCIs, the cVEP trials of the first 3 runs were applied to the model and targets were predicted. Because each trial consists of 3 cVEP cycles, each cycle is predicted separately, meaning that each run has $3 \cdot 32 = 96$ trials. Averaged over all subjects, the accuracy is 60.6%. The results for a bit-wise prediction on the c-VEP dataset are shown in Fig. 5 for each subject, it is worth noting that subject S4 achieved an average accuracy of 66.3% of correctly predicted bits, which implies an average ITR of 281.1 bpm. The prediction of the cVEP m-sequence, can be predicted significantly better than the random sequences ($p<0.005$).
The results of the target prediction using the euclidean distance are shown in Tab. 3 including a comparison to the to the rVEP stimulation. On average, 60.6% of all targets were predicted correctly, resulting in an ITR of 64.3 bpm with an inter-trial time of 1s.

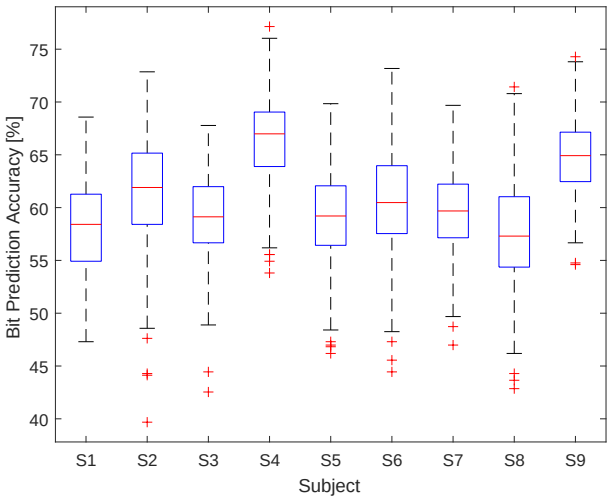

Figure 5: Prediction of the cVEP targets' modulated bit sequences. For each subject S1 to S9, the bit prediction accuracies of all 288 cVEP trials are plotted.

DISCUSSION

In this work, a novel method to classify VEPs is evaluated. While previous methods make use of special modulation codes, i.e. with a low auto-correlation, to achieve the maximum performance, we pursued a different approach. We want to address the "overlapping" VEP behavior from the ground. Since the assumption of linearity of VEP generation is investigated by several other studies [12,13], we proposed a new method based on linear ridge regression. Using random codes, we assume to cover most of the possible "overlapping" VEPs in order to predict arbitrary modulation sequences afterwards. Aside from this, the method has several advantages: trials can have an arbitrary length, phase-lock is not required (like it is for m-sequences), and the number of targets can be chosen arbitrary.
With an average ITR of 86.5 bpm, our model proves that it is possible to reconstruct arbitrary unseen (random) modulation sequences with an average accuracy of 59.1% (without repetition). Surprisingly, the prediction of the cVEP m-sequence, can be predicted significantly better with an average accuracy of 60.6% and up to an ITR of 281.1 bpm. This could be due to the low auto-correlation of the m-sequence and proves clearly that our model is also able to handle cVEP modulation, although it never has seen the m-sequence during the training phase.
As mentioned before, we loose information by using a simple threshold to construct the bit sequence. This effect can also be seen in the results of the target prediction, where the ITR is 27.2 bpm lower compared to the bit prediction. But part of this difference might also be attributed to some general problems of using ITR. By using the euclidean distance to target prediction, the ITR drops significantly less (15.6 bpm), and is therefore recommended for BCI control.
Interestingly, the variance between the subjects is very high. While two subjects achieved a poor accuracy during the whole experiment with ITRs of lower 30 bpm, two other subjects achieved average ITRs of always above 114 bpm and up to 281.1 bpm. This variance could be caused by problems during the EEG preparation and/or because of some subjects wearing glasses.
Using either the rVEP modulation or cVEP modulation, our method also performed better than the re-convolution BBVEP of Thielen *et al.* [10] which achieved an average ITR of 48.4 bpm using their early-stopping trials.

CONCLUSION

In this paper, we have introduced the rVEP BCI, a new approach to predict arbitrary VEP modulation sequences based on random sequence learning. We showed that our model was able to predict bits of fully random sequences as well as m-sequences. The model predicts random sequences with an average accuracy of 59.1% and m-sequence with an average accuracy of 60.7%. Surprisingly, the average ITR of the m-sequence prediction of S4, excluding the inter-trial time, amounts to 281.1 bpm although the model has never seen the m-sequence before. This clarifies the capability of our rVEP BCI. Also it is quite interesting why m-sequences can be predicted significantly better than random sequences, although the model was trained on random sequences. This could be due to the low auto-correlation or the amount of bit changes. We also showed that our approach can be used for BCI control with an average ITR of 64.3 bpm and up to 115.5 bpm.
In future work, the rVEP BCI will be tested in an online study. Due to the sliding window prediction, we also want to use an early-stopping method, in which a trial ends when a certain reliability-threshold is reached. Once we found a threshold the method can be applied to an asynchronous BCI, because targets will only be selected if the threshold is reached and this should only be the case if the user fixates a target. Additionally, the use of error-correcting codes could be used for stimulus modulation in order to improve the prediction.

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