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The Effect of Single Session Implicit Motor Learning on Finger Motor Imagery for EEG BCI

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ABSTRACT

Motor imagery (MI) based brain computer interfaces (BCIs) rely on cue driven paradigms, yet little is known about how the order in which cues are presented influences neural discriminability. Here the effect of sequential versus random cue order on finger-MI is investigated. Ten healthy, right-handed participants (7 F, mean age = 31.9 ± 10.7 years) completed two runs of 300 trials each (30 cycles of 5-finger trials). Across subjects, the γ-band integrals showed the most consistent cue-order effect. Depending on frequency band 7-8 subjects yielded significant effects. Participants who began with the sequential cues exhibited higher mean amplitudes and reduced variability across runs, suggesting that early exposure to a predictable cue sequence facilitates implicit motor-learning and stabilises the forward model. These findings demonstrate that cue-order manipulation is a potent factor influencing MI-BCI performance and underscore the importance of designing training protocols that promote implicit learning.

INTRODUCTION

The development of brain computer interfaces (BCIs) towards more complex systems, introduces a need to consider the effect of paradigm choice for data collection. The combined efforts of non-invasive BCI and finger movement research enables the consideration of a neurorehabilitative system that can decode imagined finger movement [1]. This is especially crucial for recovery after stroke, where the motor imagery (MI) of finger movement is still executable, but motor execution (ME) frequently is not [2]. The development towards such intricate tasks in the context of MI BCI research requires the evaluation of each aspect that affects the data discriminability in a classification context.

The neural nature of individual finger movement is complex and delicate. Pioneering studies utilising invasive recording methodology such as electrocorticography (ECoG) have allowed for initial analysis of the neural correlates underlying contextual ME and MI [3]. However, invasive recording is not feasible or even possible for all required implementations of finger movement analysis. In the context of neurorehabilitation for example a non-invasive approach such as electroencephalography (EEG) is more feasible as it is comparatively low in cost and recovery efforts. Despite drawbacks such as low signal to noise ratio (SNR) and decreased spatial resolution, EEG has been successfully implemented for finger movement studies [4].

Established feature extraction methodologies such as filter bank common spatial patterns (FBCSP) have shown moderate success in a variety of EEG BCI studies for finger movement [5]. Drawing from these observations, it is possible that the delicate nature of finger movement requires to branch out and explore feature patterns outside the status quo. Especially where the essence of MI studies must be considered, as event initiation and execution are not as controllable as for ME.

Understanding the physiological nature underlying finger movement and how it is recorded in EEG, is important to consider for feature engineering approaches. Where the impact of implicit motor skill learning has been assessed in paradigms such as the serial reaction time tasks, the effect on imagined finger movement has not been contemplated [6]. As such this paper focuses on determining the effect of randomly versus sequentially cued finger MI instructions within a single session design. Specifically focusing on the potential effect of participants being introduced to the overall task with either random or sequential cue order. This permits to consider the effect of implicit motor learning in the context of finger MI. Implicit motor learning refers to the gradual and unconscious sensorimotor mapping that occurs during familiarisation with instruction patterns [7]. This ties into the predictive coding models that assume that predictability leads to heightened β-band synchrony and α-band inhibition [8].

The hypothesis addressed in this paper is that participants introduced to the task with sequential cue order will show less discriminability between cue orders The research question considered whether cue order has a significant effect on implicit motor learning for finger movement MI tasks.

MATERIALS AND METHODS

Dataset:

A total number of 10 right-handed subjects was recruited (7 women, mean age 31.9, SD = 10.7) to participate in a single session EEG MI task. Prior to EEG cap application

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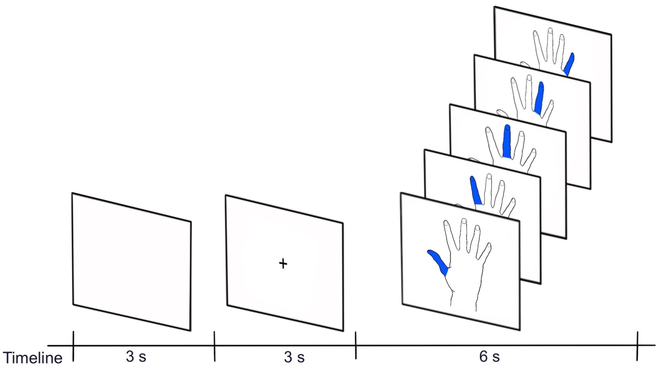

Figure 1: Sequential cue order instructions for finger MI.

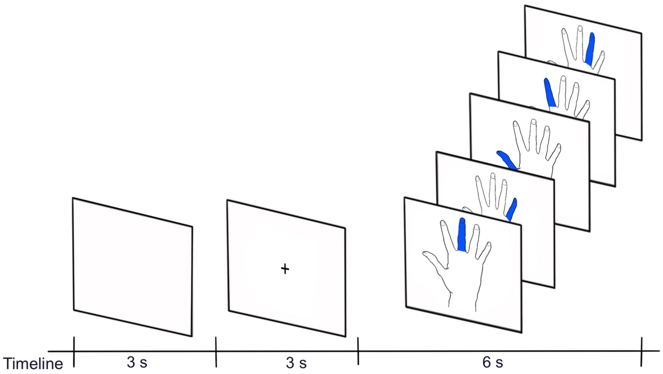

Figure 2: Random cue order instructions for finger MI.

participants were informed about the proceedings of the test as well as potential risks to provide informed consent. The EEG data was amplified via the g.tec HiAmp which was connected to a laptop via USB-A [9]. The recording was executed with 64 g.Scarabeo active Ag/AgCl electrodes of which 2 were placed on the mastoids as reference. Electrode placement was done with the international 10-10 system, the locations of which where associated with the electrode number during processing. Here the recording loop was build in Simulink incorporating g.tec's acquisition system for accurate recording. The paradigm presentation was initialised within the recording loop to allow for maximal alignment at a sampling rate of 512 Hz.

Each subject completed 30 cycles of 5 finger trials for each cue order, leading to 300 trials per subject. Each cue order was separated into two 15 minute cycles between which participants had a short break. Each individual finger trial was initialised with a 3 second white screen, followed by a 3 seconds of focus cross prior to the event initialisation visual which lasted for 6 seconds. A visualisation of a single trial run is given in Fig. 1 for sequential cue order and Fig. 2 for random cue order. The cue order specifically refers to the order in which each finger was presented to the participants within a single trial. Meaning sequential cues were ordered in thumb, index, middle, ring, and pinky for each trial, while random cues were in different order for each trial. When switching to the next cue order participants were given several minutes of rest.

Subject	Run 1	Run 2
1	Sequential	Random
2	Random	Sequential
3	Sequential	Random
4	Random	Sequential
5	Sequential	Random
6	Sequential	Random
7	Random	Sequential
8	Random	Sequential
9	Sequential	Random
10	Random	Sequential

Table 1: Subjects and the cue of each run.

The order in which each subject was presented with the paradigm was interchangeably controlled to assess any potential effects of exposure to random or sequential in the first run where Table 1 shows the order for each subject.

Analysis:

Prior to feature extraction and analysis the EEG data was preprocessed. A bandpass filter of 0.5 to 45 Hz was applied to filter out noise as is standard practice for EEG preprocessing. In the same vein, common average referencing (CAR) was utilised for offline re-referencing, before the data was segmented into epochs with a 7 second length. This included 2 seconds of pre-event data and a 5 second post-event data. This was repeated for each run and order and executed using the *mne* python library [10] The epoched data was analysed with a sliding window integral moving across each epoch: Here the EEG data was initially bandpass filtered to analyse the individual frequency bands of alpha, beta, gamma, and theta. Each window was the same length as the sampling frequency of 512 Hz, where an overlap of 256 samples permitted to consider transient changes within each window:

$$I_n = \int_{\frac{n\,\mathrm{step}}{f_s}}^{\frac{n\,\mathrm{step}+L_{\mathrm{win}}}{f_s}} \left| x(t) \right| \tag{1}$$

where the trapezoid weighting was considered:

$$\mathrm{d}t \approx \Delta t \left[\frac{1}{2}\left|x_{n\,\mathrm{step}}\right| + \sum_{k=1}^{L_{\mathrm{win}}-2} \left|x_{n\,\mathrm{step}+k}\right| + \frac{1}{2}\left|x_{n\,\mathrm{step}+L_{\mathrm{win}}-1}\right| \right] \tag{2}$$

where $\Delta t = 1/f_s$ and $\mathrm{step} = L_{\mathrm{win}} - 256$.

For equation 1 each channel and label was assessed individually. In equation 2 the first and last step of the discrete timeframe were weighted to consider transient changes across each window. This process created a dataframe containing epoch number, finger label, frequency band, channel, window index, and the associated integral value informing about the summed area under the curve in this window. This detailed dataframe enabled an in-depth analysis of the differences between cue order and between runs. For cue order analysis it was first determined if the data at hand was normally distributed, which allowed for ANOVA measurement. If the data was not normally distributed Kruskal-Wallis was applied.

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The significance levels were corrected with the bonferroni method to ensure validity of the results in the face of repeated measures. For analysis of the discrepancies between runs either a paired t-test for normally distributed data or a Wilcoxon Signed Rank (WSR) for non-normally distributed data was used. All of the code utilised for statistical analysis was taken from the *statsmodels* python library [11].

RESULTS

The analysis of differentiability between fingers based on sliding window integral activity found that no significant difference occurred between fingers. This indicates that all five fingers iniate correlated temporal-spectral patterns.

Orderwise Comparison:

This section contains Tables 2 through 5 considering the effect of random versus sequential order independent of the order it was introduced to the participants. As such the effect of the order alone and if it had a significant impact was considered. For the θ-, α- and β-band 7 out 10 subjects yielded significant difference between orders. For the γ-band 8 out of 10 subjects were significant. Notably across all four bands only one subject S5 consistently showed no significant difference between cue orders.

Subject	H Value	Corrected P
1	1.94	0.66
2	23.19	0.00
3	129.33	0.00
4	134.82	0.00
5	1.69	0.78
6	10.5	0.01
7	66.31	0.00
8	124.27	0.00
9	5.19	0.09
10	20.92	0.00

Table 2: Kruskal-Wallis analysis of the α-band sliding window integral differences between sequential and random cue order.

Subject	H Value	Corrected P
1	64.68	0.00
2	8.02	0.00
3	98.2	0.00
4	134.92	0.00
5	0.29	1.00
6	69.93	0.00
7	48.06	0.00
8	133.76	0.00
9	1.98	0.64
10	2.32	0.5

Table 3: Kruskal-Wallis analysis of the β-band sliding window integral differences between sequential and random cue order.

Runwise Comparison:

Subject	H Value	Corrected P
1	56.6	0.00
2	38.15	0.00
3	50.78	0.00
4	135.03	0.00
5	3.17	0.3
6*	64.88	0.00
7	92.66	0.00
8	139.75	0.00
9	10.75	0.00
10	0.46	1.00

Table 4: Kruskal-Wallis analysis of the γ-band sliding window integral differences between sequential and random cue order. Subject S6 was normally distributed in this band and ANOVA was applied.

Subject	H Value	Corrected P
1	12.77	0.00
2	18.56	0.00
3	138.86	0.00
4	106.06	0.00
5	0.29	1.0
6	2.12	0.58
7	79.18	0.00
8	93.29	0.00
9	11.49	0.00
10	4.88	1.00

Table 5: Kruskal-Wallis analysis of the θ-band sliding window integral differences between sequential and random cue order.

Where the previous section showcased the results of indiscriminately analysing differences between cue orders, this section considers cue order introduction. Here Figures 3 and 4, consisting of eight plots, visualise the effect of random versus sequential cue order as first task introduction. Specifically how each frequency band was impacted and how the mean sliding window integral for each subject differs between runs. Noticeably, the subjects who started with random order showcased a significant difference between order runs compared to those who started with sequential. Most display an increase in mean integral value when engaging with the sequential cue order as their second run. This distinction was not as strong in those who started with sequential and had random as their second run, where only S3 showcases significant change.

DISCUSSION

This paper sought out consider how cue order affects implicit MI learning for finger movement, where the main hypotheses cannot be rejected. Participants introduced to sequential cue order first overall elicited stronger signals that were more stable across the two cue orders, where a significant difference between them was given in all but one subject.

When examining Tables 2 through 5 it is discernable that most subjects experience significant difference across cue order in at least one of the frequency bands. What stands

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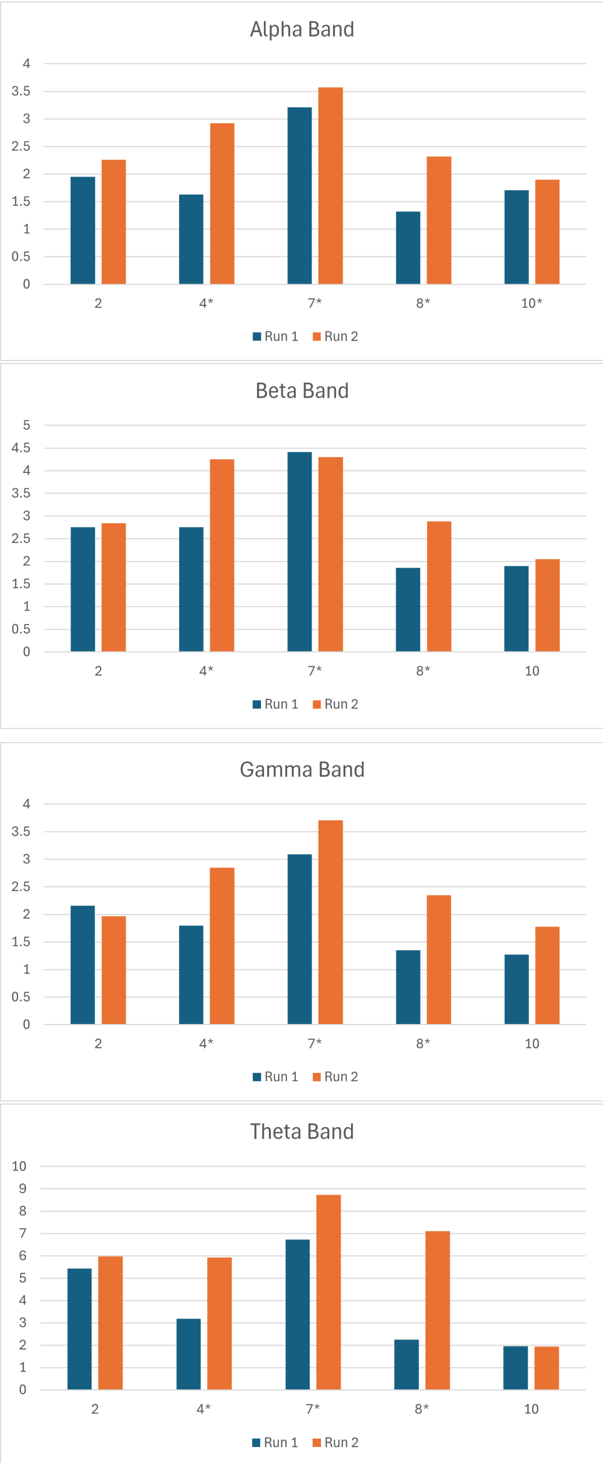

Figure 3: Sliding-window integral mean for each frequency band ($\alpha, \beta, \gamma, \theta$) separated by run order where subjects first executed **random order**. The y-axis holds the signal amplitude in that band. An asterisk (*) marks a statistically significant difference between runs.

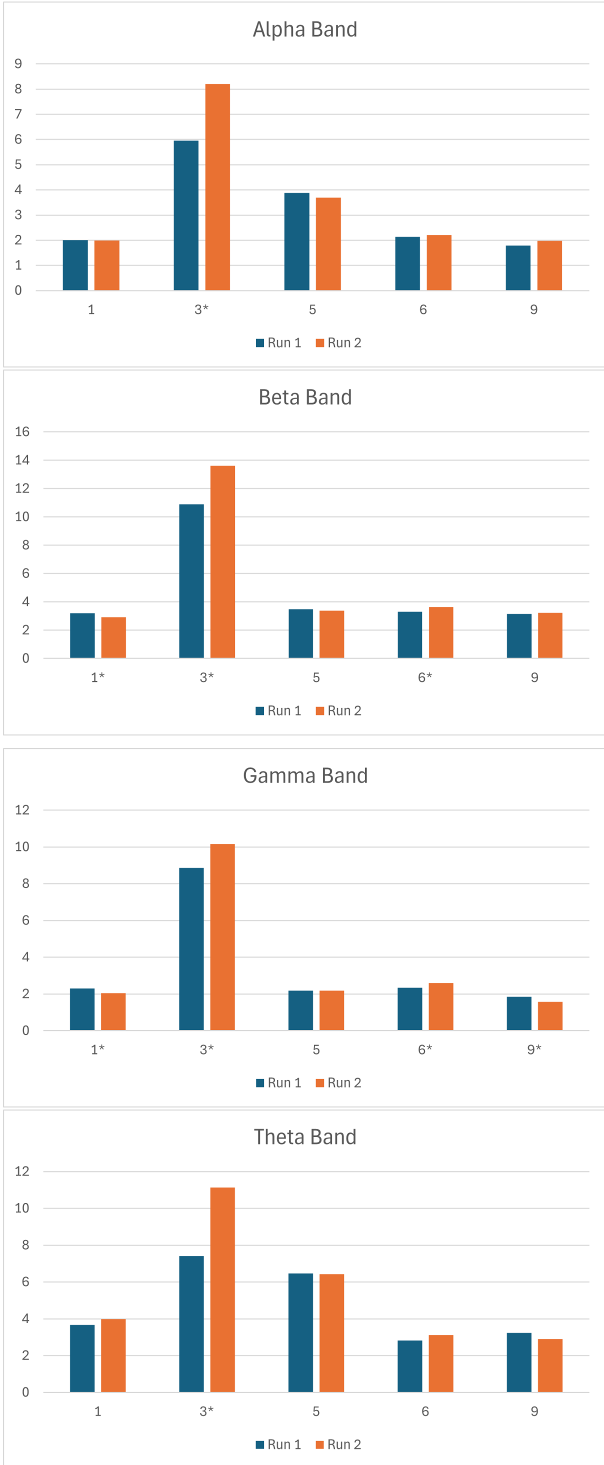

Figure 4: Sliding-window integral mean for each frequency band ($\alpha, \beta, \gamma, \theta$) separated by run order where subjects first executed **sequential order**. The y-axis holds the signal amplitude in that band. An asterisk (*) marks a statistically significant difference between runs.

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out is that the α- and β-band discriminability is not as strong as anticipated for every subject. Instead most subjects demonstrate cue order effect in the γ-band. The relevance of the γ frequency band for finger movement has been demonstrated, where the effect of cue order mirrors this [12].

An important observation is that the subjects who did not demonstrate a cue order effect in α- or β-band show a significant effect in the γ- and θ-band, see subjects S1 and S9. In a similar vein, subjects whose γ- and θ-band did not allow for significant differentiability demonstrate it in α- and β-band. Especially subject S1 stands out, where only the α-band reports a significant effect.

The effect that introduction order can have on the discernability between cue orders is visualised in Figures 3 and 4. Here it is shown that random cue order as task introduction potentially inhibits the forward model to develop reliable sensorimotor mapping. As such it is reasonable to consider that the task introduction cue order has a significant impact on the overall performance. This is mirrored in the strength mean power compared between sequential and random across all bands as demonstrated in Figure 4. In direct comparison to Figure 3 where differences between Run 1 and Run 2 are more commonly significant and stronger overall. For participants who were introduced via sequential order only subject S3 performed consistently with discriminability across cue orders, signifying a stronger forward model initiation.

The nature of the data at hand allows for detailed temporal-spectral analysis of the amplitude power within each frequency band. This permits to infer underlying neural behaviour, such as synchronisation and desynchronisation patterns [13]. The mean amplitude reported for the β-band for example demonstrates a stronger amplitude in the β-band for those who did the sequential order in their first runs. In contrast, those exposed to random order first achieved significantly lower mean amplitude. This mirrors the expected event related synchronisation (ERS) and desynchronisation (ERD) patterns associated with task familiarity and implicit motor learning [14]. This behaviour is mirrored across all frequency bands, indicating that while the discriminability might not always be significant, the ERDS behaviour mirrors known physiological patterns.

In the context of EEG BCI for finger movement decoding these results allow to determine the positive effect of sequential task presentation. This is extrapolated from the mean amplitude achieved for those who started with sequential cue order. Furthermore, the low discriminability between cue orders if started with sequential showcases the reliability of signal over task adaptability.

Future research must consider how to utilise this observed effect to extrapolate delicate patterns such as finger MI more reliably. While no observed effect could be reported between fingers for sliding window integrals in this instance, the information on cue order effect on implicit motor learning enables the development of a stronger effect paradigm.

CONCLUSION

This paper examined the effect of cue order on delicate MI tasks, specifically for the temporal-spectral domain. The results allow for future feature engineering to consider temporal effects of neural behaviour. Specifically, that sequential cue order as introduction to a task promotes implicit motor learning in comparison to random cue introduction.

ETHICS AND FUNDING

The data used in this paper was collected with approval of the UCL Humanities, Arts and Sciences Research Ethics Committee. Ethics approval number: 26907/001. This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) grant EP/S022139/1 - The Centre for Doctoral Training in Connected Electronic and Photonic Systems.

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