

## Motor imagery versus reality in gymnastics: A pilot field-study using mobile EEG when initiating basic skills on the horizontal bar

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### Abstract:

Defining the "functional equivalence" between motor imagery (MI) and the actual dynamic execution of a motor task is of crucial importance. Achieving this understanding may enable artifact-free neuroscience of sporting behaviour, consequently facilitating big data pattern recognition to decode and predict motor behaviour. To date, however, limited field studies have delved into the neuronal behaviour of dynamic sport-specific motor tasks, particularly those involving acyclic movements. This pilot study sought to address this gap by exploring the limits of sport-specific EEG field research. Mobile EEG/EMG setups has been utilised to examine experienced gymnasts' imagined and actual movement initiation when performing basic horizontal bar elements. By doing so, the aim was to elucidate the degree of computational equivalence between MI and actual movement initiation, and identify the factors that contribute to discrepancies in neural activation patterns. The main findings suggest that MI exhibits a level of computational equivalence that approaches internal simulation processing, but falls short of being able to fully analyse sport-specific tasks without actual execution. Factors such as arousal, activation, proprioceptive demand, motor unit recruitment speed, and the sensorimotor modality were found to affect motor-related alpha/beta activity levels. These factors may contribute to the observed differences between MI and actual task execution. In conclusion, additional investigation and the implementation of standardised procedures are essential to overcome movement artifacts and accurately record real-world performances. By addressing these challenges, we can initiate a novel epoch of machine learning-based human movement neuroscience, with far-reaching implications for the optimisation of athletic training, rehabilitation, and the understanding of human motor control. Ultimately, our study lays the groundwork for further research aimed at refining the concept of functional equivalence between MI and actual motor task execution in the context of dynamic sport-specific movements.

**Keywords:** alpha/beta oscillation, EMG, movement initiation, sensory information

### Introduction

Decoding neuronal motor behaviour becomes a key element to fuel exponential growth in human technology. With evolving metaverses, quantum computing and artificial intelligence (AI) the world lunges at the translation of brain activity. Daly (2023) recently demonstrated that musical features such as rhythm, melody, and harmony can be reliably decoded from neural activity patterns. As it is assumed that imagined and executed movements also share similar brain activation patterns (Grezes and Decety, 2001; Héту et al., 2013), the potential of advancing technology to provide new insights in human movement neuroscience is vast. For example, online electroencephalography (EEG) recordings could be amplified by a bidirectional brain-to-cloud connection that is systematically analysed by artificial intelligence (AI) (e.g., big data analytics).

However, to date, few studies have explored the neuronal behaviour of sport-specific movements in the field to question the prevailing (lab-based) consensus. Although facilitated by recent developments in mobile EEG technology, moving out of the lab is still very challenging due to several limitations, including the absence of standardised methods, movement artifacts, and spatial resolution (Keil et al., 2022; Reis et al., 2014; Thompson et al., 2008). By extracting oscillatory motor task signatures from lab-based setups, this study departs from the conventional approach in order to investigate real-world sport performances and compare its equivalence to motor imagery.

Thus, in previous studies, consecutive motor tasks were initially designed to cover signatures from transferable movement parameters (e.g., rate of force development, contraction duration, muscle contraction vs. relaxation) (Flüthmann et al., 2019; 2022; Skrzeba and Vogt, 2018). Building upon this foundation, we report pilot trials of associated horizontal bar gymnastics combined with motor imagery and a mobile EEG/EMG setup. Movement-related electrophysiological activity obtained in response to almost any preparation task or movement onset is associated with decreasing activity (i.e., desynchronising; (Pfurtscheller & Lopes da Silva, 1999; Ramos-Murguialday and Birbaumer, 2015). Surprisingly though, ballistic motor tasks were found to be accompanied by increasing neuronal activity (i.e., synchronisation), whereas tasks requiring constant feedback

-----1253

(i.e., proprioception demanding tasks) showed neuronal desynchronisation (Flüthmann et al., 2022). Cross-frequency interaction is believed to provide a unified mechanism to initiate and conduct such complex (motor) processing. For instance, alpha (or mu-rhythm over motor areas; 8-13 Hz) synchronisation is suggested to provide pulsed inhibition, timing, and selective gating of target information (Cheron et al., 2016; Klimesch et al., 2007; Klimesch, 2012; Jensen and Mazaheri, 2010), while beta (14-30 Hz) desynchronisation may functionally link relevant brain regions to allow binding and transient input (Hosaka et al., 2015; Kuo et al., 2014; Lebedev and Wise, 2000; Sugata et al., 2020). This process involves sensory predictions that are suggested to provide efficient adjustment of motor commands and remain calibrated through constant adaptation from prediction errors (Franklin and Wolpert, 2011). In a theoretical interpretation alpha and beta oscillations might be indicative of the constant interaction between feedback and feedforward control, as suggested by the Optimal Feedback Control (OFC) theory (Todorov, 2004). The feedforward control component utilises an internal model of the body and its environment to produce an initial motor command. Concurrently, the feedback component adjusts this motor command according to sensory feedback, thereby correcting for potential errors. The desynchronisation of brain oscillations during sensorimotor tasks could be a reflection of this dynamic feedback and feedforward control process, which facilitates efficient and precise execution of movements. This observation aligns with the role of beta oscillations in maintaining the current sensorimotor or cognitive state (Engel and Fries, 2010), highlighting the role of brain oscillatory activity in motor control. Thus, studying these oscillations can provide critical insights into the neuronal underpinnings of dynamic motor actions and may also aid in understanding their functional interaction.

Interestingly, imagined self-touch was found to induce the same desynchronisation as the real tactile feedback (Kilteni et al., 2018), although its internal nature impedes constant visuo-motor adaptation. Whether such evidence can be found in more complex, consecutive movements outside the lab remains to be seen. Motor imagery (MI) is defined as a neuronal process during which an individual mentally stimulates a physical action (Jeannerod, 1994). Although research has identified many neural similarities between imagined and executed motor execution (Jeannerod, 1994; Papaxanthis et al., 2002), verifying the computational equivalence is challenging. Not only are control and task conditions difficult to generalise, the modality (first vs. third person view), instruction (single vs. consecutive MI), laterality, and surroundings also influence the underlying neuronal behaviour (Héту et al., 2013). To standardise motor imagery experiment protocols, first ensure participants receive clear, uniform instructions regarding perspective and task type. Second, provide preliminary training for participants, using guided imagery or supervised mental practice to reinforce understanding and accurate execution of MI. Lastly, verify participant's MI ability through subjective and objective measures, and confirm engagement of the correct neural pathways via neuroimaging techniques like EEG. To tackle these issues and explore if similar evidence can be found in more intricate, sequential movements outside the laboratory setting, standardising MI experimental protocols becomes imperative.

Therefore, the purpose of this pilot study was to investigate the initiation of imagined versus executed sport-specific tasks by comparing the respective motor-related brain oscillations. To test our hypothesis that MI shows similar alpha and beta activity adaptation as field tasks do, we examined the (imagined) initiation of basic horizontal bar elements while exploring the limits of sport-specific EEG field research. Specifically, we examined alpha and beta activity in experienced gymnasts initiating the glide kip, slow back hip pullover and back hip circle element under field and imagery conditions. With this approach, the aim is to cover a wider range of realistic sport-specific movement characteristics, discover boundaries, and, thus, further understand underlying neuronal mechanisms.

## Materials and Methods

### *Participants*

Ten healthy gymnasts (6 males, 4 females,  $22.4 \pm 3.3$  years,  $170.1 \pm 7.7$  cm,  $67.2 \pm 10.3$  kg) with no neurological or musculoskeletal disorders were recruited for this study. All participants were experienced gymnasts ( $16 \pm 9.4$  years of experience) to ensure clean element execution and avoid fatigue throughout the measurement. Informed consent was provided prior to testing. The experimental study was conducted at the German Sport University Cologne and approved by the Human Research Ethics Committee in accordance with the Declaration of Helsinki.

### *Experimental Design*

Each participant was asked to perform 10 repetitions of 3 basic horizontal bar elements: Glide kip, slow back hip pullover and back hip circle, each ending up in front support on the bar. At the beginning of the test, the bar was positioned at shoulder height. Continuous EEG, EMG and video recordings served to determine muscle on-/offsets and movement phases. After an individual warm up, experiment familiarisation, and 6 maximal voluntary contraction (MVC) tasks, EEG baseline measurements were performed using a standardised starting position (standing upright while grabbing the bar). The following randomised protocol included 10 subsequent repetitions of each element. During a 30-second rest interval after each repetition, participants were asked to sit down and imagine themselves initiating the next repetition from a first-person view after closing their eyes. All participants were carefully instructed to avoid strong impacts, blinking and teeth grinding during movement

execution or imagination. To minimise and detect fatigue, the protocol included a two-minute break after each block and MVCs at the end of the test. The test took about one hour on average per participant. Figure 1. Horizontal bar setup for EEG/EMG/video measurements.



#### *Data Acquisition*

BrainVision Recorder 1.23 in combination with the LiveAmp Sensor and Trigger Extension (Brain Products GmbH, Germany) was set up for real time EEG, EMG and video recordings (Figure 1). To synchronise all three systems, the LED flashlight trigger that was visible for the camera induced a starting edge into the LiveAmp system while simultaneously starting the EMG recording via the DelSys trigger module (Trigno™ Wireless System, DelSys, United States).

#### *EMG recordings*

EMG data were sampled at 2000 Hz using 8 wireless sensors (Trigno™ Wireless System, DelSys, United States) positioned at relevant muscle sites (biceps brachii, triceps brachii, pectoralis major, anterior/posterior deltoid, upper trapezius, infraspinatus, latissimus dorsi; (Frère et al., 2012). All sensors were attached according to SENIAM guidelines (Merletti and Parker, 2004) and secured with sensor adhesives and tape.

#### *EEG recordings*

EEG data were sampled at 1000 Hz using a flexible actiCAP slim EEG cap, LiveAmp 32 wireless EEG amplifier and BrainVision Recorder 1.23 (Brain Products GmbH, Germany). The system was comprised of 32 active Ag-AgCl electrodes, arranged in the international 10-20 system (Jasper, 1958) at positions Fp1, Fp2, F3, F4, F7, F8, Fz, FC1, FC2, FC5, FC6, C3, C4, Cz, CP1, CP2, CP5, CP6, P3, P4, P7, P8, Pz, PO9, PO10, T7, T8, TP9, TP10, O1, O2 and Oz, each referenced to FCz. AFz served as ground electrode. PO10 was added as horizontal electrooculogram (EOG) placed at the outer canthus of the right eye to detect lateral eye movement (Flüthmann et al., 2019; Vogt et al., 2018). For optimal signal transduction, electrodes were filled with SuperVisc™ electrode gel (EasyCap, Germany) while their arrangement ensured a distance of ~25mm to each other to avoid cross-talk. Familiarisation at the beginning helped to reduce neck or facial muscle activation (i.e., teeth grinding, eye blinking) as well as impacts causing EEG artifacts. Although not measured, exceeding perspiration that may interfere with conductivity could not be observed.

#### *Data Analysis*

##### *EEG Analysis*

EEG data were processed using Brain Vision Analyzer 2.2.0 (Brain Products, Germany) and MATLAB R2021a (The MathWorks inc., USA). EEG signals were bandpass filtered between 5 and 50 Hz (time constant 0.318 seconds). Segmentation into Pre ( $t \in [-1000, 0]$ ) was either based on movement initiation (i.e., motion onset) or MI initiation (i.e., first second after the closing of the eyes) as time locking events with respect to oscillatory (alpha) reactivity (Flüthmann et al., 2019; 2022; Woertz et al., 2004). High noise movement-related segments were excluded from subsequent analysis (automatic artifact rejection; gradient  $< 100 \mu\text{V min/max}$  amplitudes  $\pm 200 \mu\text{V}$ ), so that a minimum of 8 low-impact initiation segments for each element were used for Fast Fourier Transformation (spectral analysis: resolution at 0.98 Hz, Hanning window 10%) The averaged segments were pooled into premotor cortex (PMC: F3, F4, FC1, FC2 and Fz), primary motor cortex (M1: C3, C4 and Cz), somatosensory cortex (SSC: CP1 and CP2) and posterior parietal cortex (PPC: P3, P4 and Pz; (Flüthmann et al., 2019; 2022; Vogt et al., 2018; 2017). Distinct frequency bands were exported according to the segmentation as mean activity in  $\mu\text{V}$ ; alpha (7-13 Hz) and beta (13-30 Hz). After averaging within participants, group means were calculated for each task.

##### *EMG Analysis*

EMG onsets, peaks and offsets of relevant muscles were visually identified to determine contraction/relaxation phases for each horizontal bar element. Then, for each phase, EMG activity over all

muscle sites was rectified and normalised according to time and MVC. Normalised EMG values were averaged over all subjects (Fig. 3). All EMG data were processed in EMGworks 4.8 (Delsys Inc., USA) and MATLAB R2021a (The MathWorks inc., USA)

*Statistics*

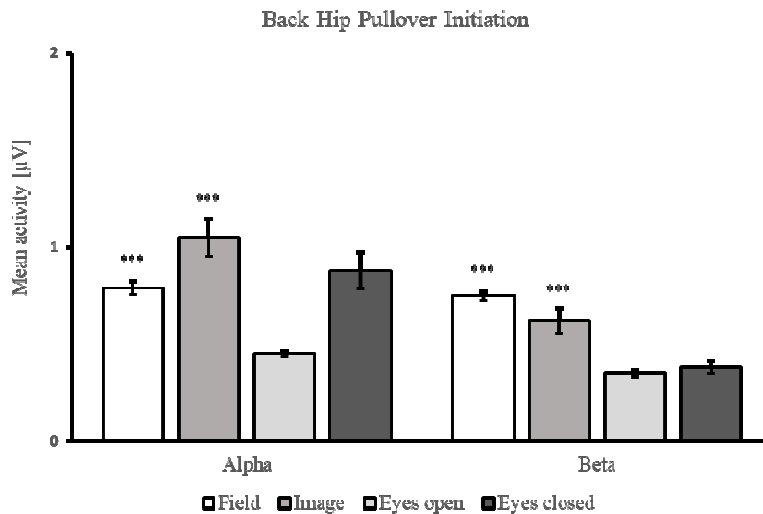
SPSS 27 (Amarok, NY, USA) and Microsoft Excel 16.0 (Microsoft Inc., USA) were used for all statistical analyses. To compare total averaged alpha and beta activity, pairwise comparisons were performed using a dependent two-tailed paired t-test. Additionally, a repeated measures analysis of variance (ANOVA) was conducted to compare alpha and beta activity between different motor areas (PMC vs. M1 vs. SSC vs. PPC). The level of significance was set at  $p < .05$ , and in cases where appropriate,  $p < .001$  was used. Finally, data are presented as group mean  $\pm$  standard error of the mean.

**Results**

*EEG activity*

All participants were able to accurately perform the prescribed horizontal bar elements without showing fatigue. Due to individual kick-off movements causing EEG artifacts, the results were limited to the isometric initiation phase of the back hip pullover element (Figure 2).

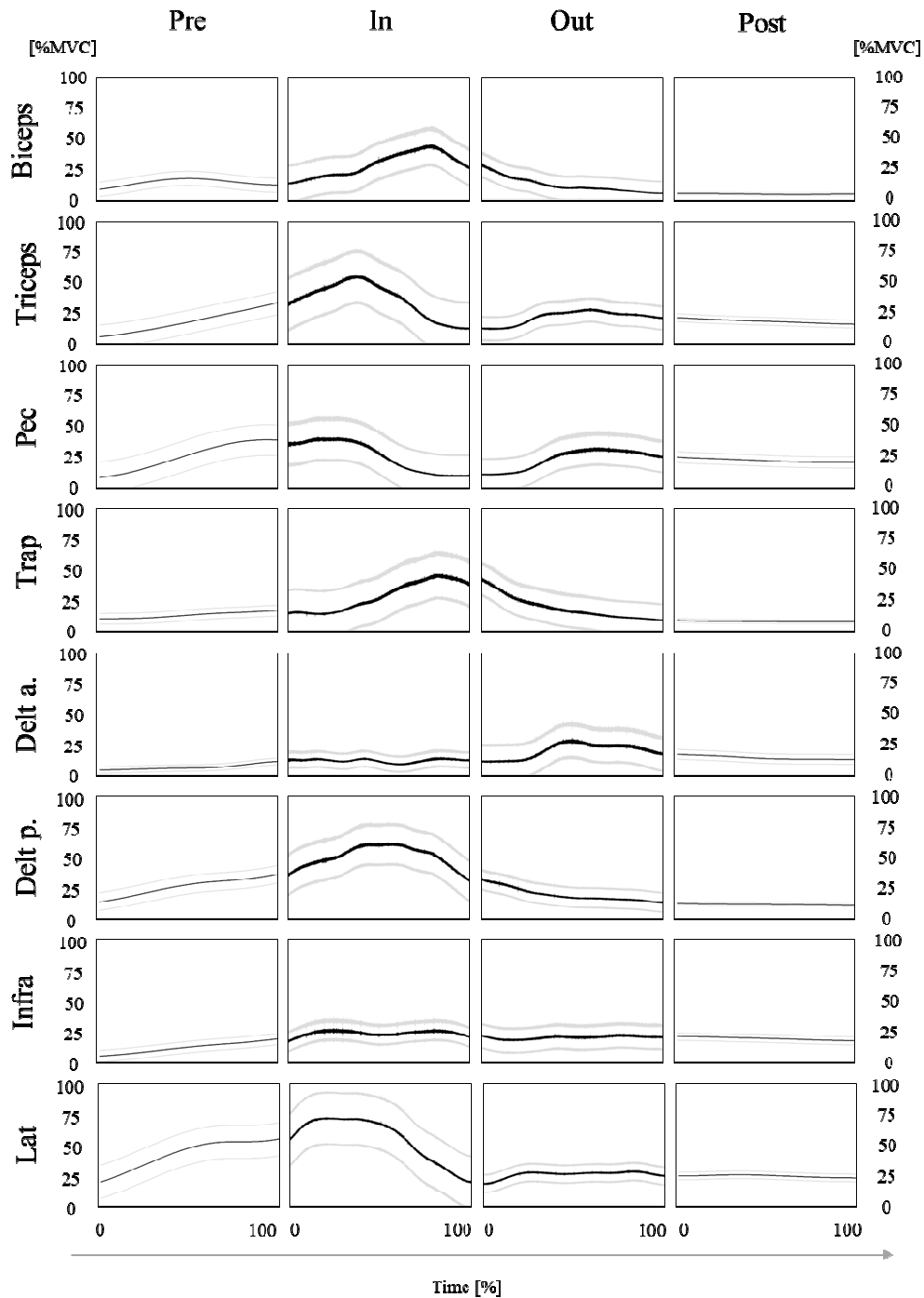
Total Pre alpha mean activity from the field ( $M = .789$ ,  $SD = .116$ ) and image ( $M = 1.049$ ,  $SD = .301$ ) condition demonstrate that direct comparability between actual sport-specific movements and its imagination is not given,  $t(499) = -22.045$ ,  $p < .001$ . The respective eyes open ( $M = .452$ ,  $SD = .043$ ) and eyes closed ( $M = .878$ ,  $SD = .296$ ) baseline condition show that despite the closure of the eyes naturally caused the largest part of the observed differences, alpha activity was significantly increased during both MI ( $t(499) = 9.752$ ,  $p < .001$ ) and the actual movement task initiation ( $t(499) = -56.291$ ,  $p < .001$ ). Total Pre beta mean activity from the field ( $M = .749$ ,  $SD = .071$ ) and image ( $M = .619$ ,  $SD = .215$ ) condition also showed increases in activity compared to the eyes open field ( $t(499) = 26.775$ ,  $p < .001$ ) and eyes closed MI ( $t(499) = 86.869$ ,  $p < .001$ ) baseline condition. Without being affected by the closure of the eyes, the field condition showed significant increased beta activity compared to MI,  $t(499) = 15,083$ ,  $p < .001$ . Areal differences were significant between motor areas ( $F(3, 3) = 2269.254$ ,  $p < .001$ ), though combined to achieve comparability with previous lab-based studies.



**Figure 1.** Mean alpha (7-13 Hz) and beta (14-30 Hz) activity ( $\mu V$ ) for field, imagery, eyes open (field baseline) and eyes closed (image baseline) condition during task initiation (onset -1 second). \*\*\* indicates highly significant differences between conditions and its respective baseline. Three levels of significance were set at  $p < .05$ ,  $p < .01$  and  $p < .001$ .

*EMG activity*

EMG data reveals the coordinated interplay of several muscle groups primarily involved in the execution of each element. The highly dynamic nature of the glide kip and back hip circle element (Figure S1 and S2), as well as individual kick-off movements, resulted in EEG movement artifacts affecting all segments except for the isometric back hip pullover movement initiation. All preparatory isometric muscle activity initiating the back hip pullover element that is related to the unaffected EEG findings above becomes visually apparent in the Pre-phase (Figure 3). Mean values of muscle activity remained steady throughout the repetitions and our athletes reported no signs of fatigue.



**Figure 3.** Displayed are normalised mean performances (black line)  $\pm$  standard deviation (light grey) of the back hip pullover element for relevant muscle sites (biceps brachii, triceps brachii, pectoralis major, upper trapezius, anterior/posterior deltoid, infraspinatus, latissimus dorsi).

### Discussion

The aim of this pilot study was to examine alpha/beta activity during the imagined and executed initiation of horizontal bar elements and, thus, explore the boundaries of sport-specific EEG field research. The primary outcome reveals that despite the limited accessibility due to movement artifacts, both conditions showed a significant increase in alpha/beta activity during the back hip pullover movement initiation. Although alpha mean activity levels differ, mainly caused by the closure of the eyes during MI, each condition exhibits a proportionate net increase in activity. This finding indicates some degree of computational equivalence between MI and its execution under field conditions. Further, it goes along with former studies suggesting MI equivalence in terms of intentions, motor planning, and initiation of motor programs (Decety and Michel, 1989;

Jeannerod, 1994, 2001; Jeannerod and Decety, 1995). Still, alpha/beta activity differences between conditions question the direct transferability of MI or lab-based findings into reality.

Given the conventional understanding of voluntary movement initiation being accompanied by decreasing activity, also known as event-related desynchronisation (ERD) (Pfurtscheller et al., 2006), the present results revealed an opposite behaviour. This may be explained by focusing on motor unit recruitment. Indeed, when comparing the back hip pullover element to oscillatory motor task signatures from prior studies (Flüthmann et al., 2019; 2022; Ofori et al., 2015), it corresponds to the behaviour observed in explosive rate of force development (RFD) conditions. Explosive RFD (or fast initiation) appears to be accompanied by task-specific synchronisation (i.e., increasing activity) while the proprioceptive demanding progression of a movement task is accompanied by desynchronisation. As movement artifacts limited the dynamic examination of all three elements, this behaviour must be confirmed in upcoming field-studies.

Alpha activity is believed to be composed of different rhythms depending on sensorimotor modalities: oscillations of the visual, auditory and sensorimotor system (Ai and Ro, 2014; Walz et al., 2015). As soon as the modality changes after the transition from open to closed eyes in MI, a thalamocortical drive may increase alpha activity to establish an inhibitory baseline that provides attentional focus and timing (Cheron et al., 2016). Framing MI as an ideal setting without perturbation may yet be another interesting thesis when comparing different levels of expertise and movement quality in future studies.

Beta oscillations are believed to be phase-locked to movement execution, serving as a coordinated template linking all commands related to the motor task (Cheron et al., 2016; Courtemanche et al., 2002; Hosaka et al., 2015; Lebedev and Wise, 2000; M. A. Lebedev and R. J. Nelson, 1995). EMG data (Figure 4) highlights the significant computational load required to link the coordination of all relevant muscle sites, providing constant estimations and readjustments during motor execution. Such increment in sensory feedback under field conditions, as well as different timings during MI may have caused the differences in beta activity between conditions.

It is widely acknowledged that the spatiotemporal principles underlying alpha/beta ERD induced by imagery and execution are similar (Kilteni et al., 2018). Top performances in certain sports may be achieved by athletes demonstrating their individual “flow” ratio between alpha and beta activity (Del Percio et al., 2010; Park et al., 2015). In this state of mind, athletes suppress all conflicting sensory input to focus solely on target information and timing. The phase of neural oscillations, indicative of alternating states of high and low cortical excitability, have been found to carry pertinent temporal information within and across brain regions (Lakatos et al., 2008). This rhythmic activity has been observed in various cortical regions and across a wide frequency spectrum, exhibiting characteristics of a hierarchical organisation. The coupling of phase and amplitude, particularly gamma amplitude with beta phase and beta amplitude with alpha phase, may potentially influence lower-frequency rhythms (Armstrong et al., 2018), thereby contributing to the process of motor planning and execution. However, understanding the exact dynamics of these oscillatory phases in the context of self-paced action remains largely unexplored, especially within the motor domain. This paucity of research points towards an intriguing avenue for future studies, aiming to enhance our understanding of the interplay between oscillatory activity and motor performance.

The level of computational equivalence of MI that we found tends towards similar internal simulation processing, but is insufficient to study sport-specific tasks without actual execution.

We suggest that increased arousal, activation, and alertness emerging in field conditions highly affect motor-related neuronal activity levels and, thus, cause the difference in mean activity. This difference may be the decisive determinant for the quality of the actual motor performance.

Sport-specific EEG field research is still in its infancy hence there are no standardised EEG methodologies. To ensure reliability and comparability, the same EEG setup as in previous lab-based studies was employed (Flüthmann et al., 2019; 2022). While the statistical methods were appropriate for this study, future studies may consider using more advanced techniques such as cluster analysis or factor analysis. Further, it should be considered using multivariate analysis techniques such as principal component analysis (PCA) or independent component analysis (ICA) to extract more complex underlying patterns from EEG data. It should be noted that hemispherical differences were not taken into account due to the chosen horizontal bar elements, which ruled out any lateralisation effects. However, this approach is limited by the lack of spatial resolution when measuring highly complex motor tasks that involve hundreds of small muscles. The present results have yet again proven the need to overcome artifacts occurring during the crucial part of sport-specific movements. Moreover, it is acknowledged that this pilot study was conducted on a small number of highly experienced gymnasts, and thus, future studies may compare their sensorimotor strategies, EMG profiles, and related kinetics with less experienced athletes to provide new insights.

We are optimistic that technological advances will put forth wireless high-resolution EEG/inertial unit sensors to study all types of dynamic movements. One promising approach is the use of inkjet-based “tattoo electrodes,” which are suitable for long-term EEG measurements (Ferrari et al., 2020).

In summary, future studies should focus on standardised methodologies and databases (Keil et al., 2022) to successfully move outside the lab, capture real-world movements, and unleash the power of computer driven analyses.

## Conclusion

This pilot study underlines the promising application of mobile EEG field research in sport-specific contexts. Our findings suggest a level of computational equivalence between Motor Imagery and actual motor execution, despite differences in alpha/beta activity. This expands our understanding of alpha and beta oscillations during imagined and executed initiation of sport-specific movements. Despite challenges due to movement artifacts, the results encourage future exploration in the motor domain, especially considering the role of oscillatory phases in voluntary movement. This research serves as a stepping stone towards more advanced, real-world EEG studies, with a potential to significantly impact athletic training and performance enhancement strategies.

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## Declaration of interest and data availability

All authors declare no actual or potential conflict of interest, including any financial, personal or other relationships with other people or organisations that could inappropriately influence, or be perceived to influence, the publication of this work. The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

## References

- Ai, L. & Ro, T. (2014). The phase of prestimulus alpha oscillations affects tactile perception. *Journal of Neurophysiology*, *111*(6), 1300–1307. <https://doi.org/10.1152/jn.00125.2013>
- Armstrong, S., Sale, M. V. & Cunnington, R. (2018). Neural Oscillations and the Initiation of Voluntary Movement. *Frontiers in Psychology*, *9*, 2509. <https://doi.org/10.3389/fpsyg.2018.02509>
- Cheron, G., Petit, G., Cheron, J., Leroy, A., Cebolla, A., Cevallos, C. et al. (2016). Brain Oscillations in Sport: Toward EEG Biomarkers of Performance. *Frontiers in Psychology*, *7*, 246. <https://doi.org/10.3389/fpsyg.2016.00246>
- Courtemanche, R., Pellerin, J.-P. & Lamarre, Y. (2002). Local field potential oscillations in primate cerebellar cortex: modulation during active and passive expectancy. *Journal of Neurophysiology*, *88*(2), 771–782. <https://doi.org/10.1152/jn.2002.88.2.771>
- Daly, I. (2023). Neural decoding of music from the EEG. *Scientific Reports*, *13*(1), 624. <https://doi.org/10.1038/s41598-022-27361-x>
- Decety, J. & Michel, F. (1989). Comparative analysis of actual and mental movement times in two graphic tasks. *Brain and Cognition*, *11*(1), 87–97. [https://doi.org/10.1016/0278-2626\(89\)90007-9](https://doi.org/10.1016/0278-2626(89)90007-9)
- Del Percio, C., Infarinato, F., Iacoboni, M., Marzano, N., Soricelli, A., Aschieri, P. et al. (2010). Movement-related desynchronization of alpha rhythms is lower in athletes than non-athletes: a high-resolution EEG study. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *121*(4), 482–491. <https://doi.org/10.1016/j.clinph.2009.12.004>
- Engel, A. K. & Fries, P. (2010). Beta-band oscillations--signalling the status quo? *Current Opinion in Neurobiology*, *20*(2), 156–165. <https://doi.org/10.1016/j.conb.2010.02.015>
- Ferrari, L. M., Ismailov, U., Badier, J.-M., Greco, F. & Ismailova, E. (2020). Conducting polymer tattoo electrodes in clinical electro- and magneto-encephalography. *npj Flexible Electronics*, *4*(1). <https://doi.org/10.1038/s41528-020-0067-z>
- Flüthmann, N., Kato, K., Bloch, O., Kanosue, K. & Vogt, T. (2019). Effects of longer vs. shorter timed movement sequences on alpha motor inhibition when combining contractions and relaxations. *Experimental Brain Research*, *237*(1), 101–109. <https://doi.org/10.1007/s00221-018-5401-5>
- Flüthmann, N., Kato, K., Breuer, J., Bloch, O. & Vogt, T. (2022). Sports-Related Motor Processing at Different Rates of Force Development. *Journal of Motor Behavior*, 1–11. <https://doi.org/10.1080/00222895.2022.2033676>
- Franklin, D. W. & Wolpert, D. M. (2011). Computational mechanisms of sensorimotor control. *Neuron*, *72*(3), 425–442. <https://doi.org/10.1016/j.neuron.2011.10.006>
- Frère, J., Göpfert, B., Slawinski, J. & Tourny-Chollet, C. (2012). Shoulder muscles recruitment during a power backward giant swing on high bar: A wavelet-EMG-analysis. *Human Movement Science*, *31*(2), 472–485. <https://doi.org/10.1016/j.humov.2012.02.002>
- Grezes, J. & Decety, J. (2001). Functional anatomy of execution, mental simulation, observation, and verb generation of actions: A meta-analysis. *Human Brain Mapping*, *12*(1), 1–19. <https://doi.org/10.1093/cercor/bhv163>
- Héту, S., Grégoire, M., Saimpont, A., Coll, M.-P., Eugène, F., Michon, P. E. et al. (2013). The neural network of motor imagery: an ALE meta-analysis. *Neuroscience and Biobehavioral Reviews*, *37*(5), 930–949. <https://doi.org/10.1016/j.neubiorev.2013.03.017>

- Hosaka, R., Nakajima, T., Aihara, K., Yamaguchi, Y., & Mushiake, H. (2015). The Suppression of Beta Oscillations in the Primate Supplementary Motor Complex Reflects a Volatile State During the Updating of Action Sequences. *Cerebral Cortex*, 26(8), 3442–3452. <https://doi.org/10.1093/cercor/bhv163>
- Jeannerod, M. (1994). The representing brain: Neural correlates of motor intention and imagery. *Behavioral and Brain Sciences*, 17(2), 187–202. <https://doi.org/10.1017/S0140525X00034026>
- Jeannerod, M. (2001). Neural simulation of action: a unifying mechanism for motor cognition. *NeuroImage*, 14(1 Pt 2), S103–9. <https://doi.org/10.1006/nimg.2001.0832>
- Jeannerod, M. & Decety, J. (1995). Mental motor imagery: a window into the representational stages of action. *Current Opinion in Neurobiology*, 5(6), 727–732. [https://doi.org/10.1016/0959-4388\(95\)80099-9](https://doi.org/10.1016/0959-4388(95)80099-9)
- Jensen, O. & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in Human Neuroscience*, 4, 186. <https://doi.org/10.3389/fnhum.2010.00186>
- Keil, A., Bernat, E. M., Cohen, M. X., Ding, M., Fabiani, M., Gratton, G. et al. (2022). Recommendations and publication guidelines for studies using frequency domain and time-frequency domain analyses of neural time series. *Psychophysiology*, 59(5), e14052. <https://doi.org/10.1111/psyp.14052>
- Kilteni, K., Andersson, B. J., Houborg, C. & Ehrsson, H. H. (2018). Motor imagery involves predicting the sensory consequences of the imagined movement. *Nature Communications*, 9(1), 1617. <https://doi.org/10.1038/s41467-018-03989-0>
- Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, 16(12), 606–617. <https://doi.org/10.1016/j.tics.2012.10.007>
- Klimesch, W., Sauseng, P. & Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition-timing hypothesis. *Brain Research Reviews*, 53(1), 63–88. <https://doi.org/10.1016/j.brainresrev.2006.06.003>
- Kuo, C.-C., Luu, P., Morgan, K. K., Dow, M., Davey, C., Song, J. et al. (2014). Localizing movement-related primary sensorimotor cortices with multi-band EEG frequency changes and functional MRI. *PLoS One*, 9(11), e112103. <https://doi.org/10.1371/journal.pone.0112103>
- Lakatos, P., Karmos, G., Mehta, A. D., Ulbert, I. & Schroeder, C. E. (2008). Entrainment of neuronal oscillations as a mechanism of attentional selection. *Science (New York, N.Y.)*, 320(5872), 110–113. <https://doi.org/10.1126/science.1154735>
- Lebedev, M. A. & Wise, S. P. (2000). Oscillations in the premotor cortex: single-unit activity from awake, behaving monkeys. *Experimental Brain Research*, 130(2), 195–215. <https://doi.org/10.1007/s002210050022>
- M. A. Lebedev & R. J. Nelson. (1995). Rhythmically firing (20–50 Hz) neurons in monkey primary somatosensory cortex: Activity patterns during initiation of vibratory-cued hand movements. *Journal of Computational Neuroscience*, 2(4), 313–334. <https://doi.org/10.1007/BF00961443>
- Merletti, R. & Parker, P. A. (2004). Electromyography. Physiology, engineering, and noninvasive applications (IEEE Press series in biomedical engineering). Hoboken, NJ: Wiley-Interscience.
- Ofori, E., Coombes, S. A. & Vaillancourt, D. E. (2015). 3D Cortical electrophysiology of ballistic upper limb movement in humans. *NeuroImage*, 115, 30–41. <https://doi.org/10.1016/j.neuroimage.2015.04.043>
- Papaxanthis, C., Schieppati, M., Gentili, R. & Pozzo, T. (2002). Imagined and actual arm movements have similar durations when performed under different conditions of direction and mass. *Experimental Brain Research*, 143(4), 447–452. <https://doi.org/10.1007/s00221-002-1012-1>
- Park, J. L., Fairweather, M. M. & Donaldson, D. I. (2015). Making the case for mobile cognition: EEG and sports performance. *Neuroscience and Biobehavioral Reviews*, 52, 117–130. <https://doi.org/10.1016/j.neubiorev.2015.02.014>
- Pfurtscheller, G., Brunner, C., Schlögl, A. & Da Lopes Silva, F. H. (2006). Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. *NeuroImage*, 31(1), 153–159. <https://doi.org/10.1016/j.neuroimage.2005.12.003>
- Pfurtscheller, G. & Lopes da Silva, F. G. (1999). Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, 110(11), 1842–1857. [https://doi.org/10.1016/s1388-2457\(99\)00141-8](https://doi.org/10.1016/s1388-2457(99)00141-8)
- Ramos-Murguialday, A. & Birbaumer, N. (2015). Brain oscillatory signatures of motor tasks. *Journal of neurophysiology*, 113(10). <https://doi.org/10.1152/jn.00467.2013>
- Reis, P. M. R., Hebenstreit, F., Gabsteiger, F., Tschanner, V. von & Lochmann, M. (2014). Methodological aspects of EEG and body dynamics measurements during motion. *Frontiers in Human Neuroscience*, 8, 156. <https://doi.org/10.3389/fnhum.2014.00156>
- Skrzeba, C. & Vogt, T. (2018). A cross-educational approach on skill-related movement technique performance: Central neuronal motor behaviour preceding the short badminton backhand serve. *Neuroscience Letters*, 686, 155–160. <https://doi.org/10.1016/j.neulet.2018.09.005>
- Sugata, H., Yagi, K., Yazawa, S., Nagase, Y., Tsuruta, K., Ikeda, T. et al. (2020). Role of beta-band resting-state functional connectivity as a predictor of motor learning ability. *NeuroImage*, 210, 116562. <https://doi.org/10.1016/j.neuroimage.2020.116562>
- Thompson, T., Steffert, T., Ros, T., Leach, J. & Gruzelier, J. (2008). EEG applications for sport and performance. *Methods (San Diego, Calif.)*, 45(4), 279–288. <https://doi.org/10.1016/j.ymeth.2008.07.006>



- Todorov, E. (2004). Optimality principles in sensorimotor control. *Nature Neuroscience*, 7(9), 907–915. <https://doi.org/10.1038/nn1309>
- Vogt, T., Kato, K., Fluthmann, N., Bloch, O., Nakata, H. & Kanosue, K. (2018). Performance control in one consecutive motor task sequence - Approaching central neuronal motor behaviour preceding isometric contraction onsets and relaxation offsets at lower distinct torques. *Journal of Musculoskeletal & Neuronal Interactions*, 18(1), 1–8.
- Vogt, T., Kato, K., Schneider, S., Turk, S. & Kanosue, K. (2017). Central neuronal motor behaviour in skilled and less skilled novices - Approaching sports-specific movement techniques. *Human Movement Science*, 52, 151–159. <https://doi.org/10.1016/j.humov.2017.02.003>
- Walz, J. M., Goldman, R. I., Carapezza, M., Muraskin, J., Brown, T. R. & Sajda, P. (2015). Prestimulus EEG alpha oscillations modulate task-related fMRI BOLD responses to auditory stimuli. *NeuroImage*, 113, 153–163. <https://doi.org/10.1016/j.neuroimage.2015.03.028>
- Woertz, M., Pfürtscheller, G. & Klimesch, W. (2004). Alpha power dependent light stimulation: dynamics of event-related (de)synchronization in human electroencephalogram. *Brain Research. Cognitive Brain Research*, 20(2), 256–260. <https://doi.org/10.1016/j.cogbrainres.2004.03.014>