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NEURAL CORRELATES OF EXPERTISE DURING KINESTHETIC MOTOR IMAGERY: SHOULD WE REWARD MAXIMUM SMR-ERD?

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ABSTRACT: Athletes practice Kinesthetic Motor Imagery (KMI) for its many benefits. However, lack of feedback impairs regular practice. To optimise KMI efficiency, athletes can use BCIs. Whereas current BCI protocols targeting KMI abilities reward maximum desynchronisation (ERD) of sensorimotor rhythms (SMRs, 12-15Hz), the neural efficiency hypothesis raises the question “what neurophysiological markers should we reinforce?”. We hypothesised that experts' SMR-ERDs would differ from novices', in particular when imagining a mastered task. To test this hypothesis, EEG activity was recorded during KMI of bio-mechanically similar tasks: one mastered by experts only and one requiring no specific expertise. Self-reported measures based on validated questionnaires were collected to assess KMI ability and MI frequency of use and to measure their potential impact on SMR-ERD. Experts (basketball players) reported higher perceived KMI abilities than novices, but similar MI practice frequency. In addition, experts showed a stronger SMR-ERD than novices. This effect was only weakly mediated by perceived KMI ability, seeming mainly driven by sport expertise.

INTRODUCTION

In order to perform, athletes dedicate themselves to both physical and mental training. The latter can take various forms, one of them being Motor Imagery (MI), which can be defined as a “dynamic state during which one simulates an action mentally without any body movement” [1]. Previous research results have shown MI's positive impact on motor skills, allowing gains in strength [2, 3] or even movement precision [4, 5], especially when practiced in a kinesthetic way. Indeed, by remembering the associated sensations that can be felt during execution, such as muscle contraction/relaxation, body heat, pain, as well as tactile information; one can activate and reinforce similar neural networks to when actually executing the movement [6, 7]. Kinesthetic Motor Imagery (KMI) is therefore a relevant complementary tool for athletes.

However, KMI's physiological manifestations cannot directly be perceived hence providing no feedback and objectivity. Indeed, unlike physical practice where athletes can adapt execution according to the output or their body's proprioceptive feedbacks; athletes cannot directly detect brain activity modulations that occur when doing KMI and adapt their strategy. This can have detrimental consequences on athletes' motivation to diligently practice KMI as feedback is necessary to learn [8].

Because KMI is associated with an event-related desynchronisation (ERD) of sensorimotor rhythms (SMRs, 12-15 Hz) [9] it is possible to use Brain-Computer Interfaces (BCIs) and provide athletes with a real-time feedback on their brain modulations during KMI. Athletes can then visualise the employed strategy's efficiency and optimise it if needed. Moreover, three recent reviews testify that BCI training improves both the ability to self-regulate brain activity and sport performance [10–12]. Many KMI-BCI protocols reward maximum SMR-ERD [13]. This suggests we consider that growing expertise will be associated with a higher desynchronisation of neurons in the sensorimotor cortices [14]. Indeed, some related fMRI and MEG findings show greater brain activations in high ability imagers [1, 15] or even in expert athletes in comparison to novices [16]. Nonetheless, some results have suggested the existence of a neural efficiency in experts [17–19]. According to this hypothesis, experts happen to have a reduced modulation of neural activity in comparison to novices [20–22], which can be attributed to a more efficient resource distribution. This efficiency would take form of reinforced temporal and spatial stability during MI tasks [16, 20, 23]. Therefore, rewarding a maximum SMR-ERD might not be the optimal solution.

The aim of our work was to investigate the neural correlates of expertise, in sport expertise and perceived KMI expertise, thereby providing elements to contribute to the debate on what neurophysiological markers should be targeted during KMI-BCI training procedures. Our main hypothesis was that experts' SMR-ERDs would differ from those of novices, in particular when doing KMI of a mastered task. Thus, we planned an experimental design with "Expertise" (2 modalities: basketball-experts, novices; between groups) and "Task" (2 modalities: free-throw, box-reaching; within groups) as fac-

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tors. KMI ability and MI frequency of use were assessed with self-reported measures based on validated questionnaires, allowing us to observe potential differences between groups and if so, add them as co-variables in the analysis of the main hypothesis.

MATERIALS AND METHODS

Participants:

17 basketball players (M age = 20.6 years old, SD = 2.4 years; 9 women and 8 men) and 16 non-basketball players (M age = 22.7 years old, SD = 3.8 years; 8 women and 8 men) were recruited for a two-hour session. According to Edinburgh Handedness Inventory [24], 28 were right handed (M = 88.68%) and 4 were left handed (M = -77.38%). Basketball players were considered as the expert group (Exp-Gp) as it was composed of competitors from District D1 to National Ligue level whereas non-basketball players were included in the novice group (Nov-Gp) as they attested never to have taken proper basketball lessons. Novices also attested that they did not have a particular expertise in any other sport, instrument playing and video games. This inclusion criterion was to prevent them from being experts in KMI as these activities can require using sensory mental models as well. All volunteers were healthy, declared having no sensory or motor deficits and had a medium to good vision. They were also naive regarding neurofeedback. After being informed of the research aims, conditions and financial compensation, all participants gave their informed written consent. This research was approved by the French Protection of Persons' Committee (national number 2022-A00626-37).

Experimental design:

Participants were seated in front of a 27-inch computer screen and started off with two questionnaires. A modified version of the Imagery Use Questionnaire (IUQ) [25] was used to determine at which frequency participants used MI in their daily life. It consisted of items such as "To what extent do you use MI in your training/activities?" that required an answer using a 7 point Likert scale going from "Never" to "Always". The MI frequency use score was calculated with 12 items. The Motor Imagery Questionnaire-Third Version in French (MIQ-3f) [26] was also completed to assess general KMI ability. Participants were asked to execute a task (knee flexion, bust flexion, vertical jump or horizontal arm adduction), imagine it (using visual or KMI) and rate the vividness of the representation on a 7-point Likert scale. General KMI ability score was obtained by summing the 4 items relative to this MI method. A general explanatory video was then shown to give all necessary instructions regarding EEG, KMI and the protocol. The experiment (See Fig. 1) consisted of 2 blocks, one for each task to imagine, composed of a 2min resting state recording, a 3D stick avatar video, 4 runs of 10 KMI trials, where each run lasted approximately 2min30s, and a general KMI ability assessment. A single run consisted of a 30s resting state period, followed by 10 KMI trials of 10s, separated by 1 to 3s rest periods and 2s of baseline. Therefore, following instructions, a 2min baseline was recorded during which a white cross was displayed on a black screen. Participants had to fixate its center while "letting their thoughts wonder". A video then presented a 3D stick avatar executing the task to imagine in the next steps. The task could either be a basketball free throw (FreeThrow) or a box reaching action (Reaching) depending on the randomised order of conditions. The latter consisted in moving a cardboard box from a knee height shelf up to a second shelf located high enough to require from participants to be on the tip of their toes. As a familiarisation phase, participants had to execute the task and progressively reduce amplitude until ending up in a sitting position while doing KMI only. Instructions were to do KMI of the task once during the 10s trial but it could be repeated a second time if participants still had a few remaining seconds. Participants would let the experimenter know when ready and all four runs would then be recorded for Block 1, with short rest periods between them. At the end of Block 1, participants could rest and Block 2 would start as soon as participants felt ready.

EEG recordings and pre-processing:

EEG was recorded with a 32 channel (FP1, FPz, FP2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, A1, T7, C3, Cz, C4, T8, A2, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, POz, O1, Oz, O2, CPz, AFz, 10–20 system) ANT Neuro eego™sports gel headset and two amplifiers, eego™sports or eego™rt. Data was referenced to CPz, grounded to AFz and targeted channel impedance was set at 5kOhm. EEG signals were recorded via OpenVibe [27] and pre-processed with Matlab/EEGLAB [28] and Fieldtrip toolbox [29]. Offline pre-processing started with applying a 1 to 40 Hz band-pass filter and down sampling the initial data to 250 Hz. Files were then merged to end up with one file per condition per participant. At this stage, for each file, a list of bad channels was made with the EEGLAB Clean Rawdata plugin. A bad channel was considered so if i) it was flat for more than 5s, ii) its high frequency noise standard deviation was above 4 and/or iii) it's correlation value with nearby channels was higher than 0.8. However, following most recent recommendations [30] bad channels were kept and removed only after Independent Component Analysis (ICA) step. Following bad channel listing, epochs could then be determined as starting 2.5s before the cross on screen appeared and ending 0.5s after it had disappeared. ICA was then applied to the data using the EEGLAB runica algorithm and components were manually rejected according to signs of artifacted activity, caused for instance by blinking, movement or other sources of noise. Per participant, between 0 and 11 components were excluded out of 32 (M = 5.94). Finally, we removed the channels from the previously saved lists, interpolated them and re-referenced the data to average. Following pre-processing, Fieldtrip toolbox was used for time-frequency decomposition using Morlet wavelets (8-35 Hz with 1 Hz steps). Wavelet cycles were

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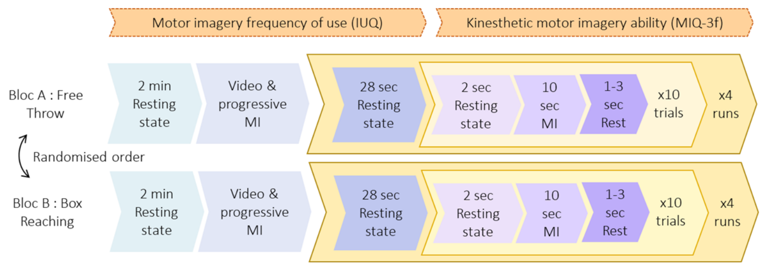

Figure 1: Session's protocol, divided in two blocs, one for each task. A bloc started with a 2min resting state EEG recording. Then, a 3D stick avatar video showed the task to imagine (FreeThrow or Reaching). Participants were asked to execute the task and progressively switch towards KMI. A run could then start with a 28s resting state recording immediately followed by 10 trials. One trial consisted of 2s of resting state, 10s of KMI and 1 to 3s of rest. A bloc was complete when 4 runs were recorded.

increased by 0.1 at each frequency, starting from a width of 3 to 5.7 to ensure a balance between sufficient temporal resolution at lower frequencies and frequency resolution at higher frequencies. As our focus was on SMRs, data from 12 to 15 Hz was then extracted before being normalised. To do so, we measured the relative change from the averaged 10 periods (1s pre-trial) of all trials of a run (1.5–2.5s of the total epoch). The last step consisted in rejecting outliers above or under Median±3*Median Average Deviation [31].

Analysis:

For the behavioural data, two t Tests were used to compare groups' IUQ MI frequency use and MIQ-3f KMI general ability scores. In order to investigate the SMR-ERD power evolution associated to an expertise level and its potential link with general KMI ability, a two-way ANCOVA for repeated measures was performed. Group (Exp-Gp, Nov-Gp) and Task (FreeThrow, Reaching) were used as independent variables, SMR-ERD power as a dependent variable and kinesthetic MIQ-3f score as a co-variable. Effect sizes are reported with a partial eta squared ($\eta^2 p$) for the ANCOVA and with Cohen's d for t Tests. Statistical analyses were computed using Jamovi v.2.4.11.0 [32], a software that implements R statistical language [33].

RESULTS

Because of a technical issue, two participants had to be excluded from the analyses. Therefore, both groups were composed of 16 participants. We also had one Exp-Gp participant with 10 missing trials out of 40 and another one with 2 missing trials. Considering the low proportion, they were included anyway.

MI frequency use:

A Shapiro-Wilk test revealed that no violation of the assumption of normality was made for MI frequency use scores (W = 0.969, p = 0.464). Thus, we performed a parametric t-test (See Fig. 2) that showed no significant difference between groups concerning the MI frequency of use [(t(1,16) = 1.18, p = 0.246, d = 0.418; Exp-Gp (M = 3.11/14); Nov-Gp (M = 2.55/14)].

General KMI ability:

For general KMI ability, Shapiro-Wilk test confirmed data was normally distributed (W = 0.969, p = 0.476). A t Test (See Fig. 2) showed significant difference between groups (t(1,16) = 2.09, p = 0.045, d = 0.739), with Exp-Gp score (M = 20.9) being significantly higher than Nov-Gp score (M = 17.7).

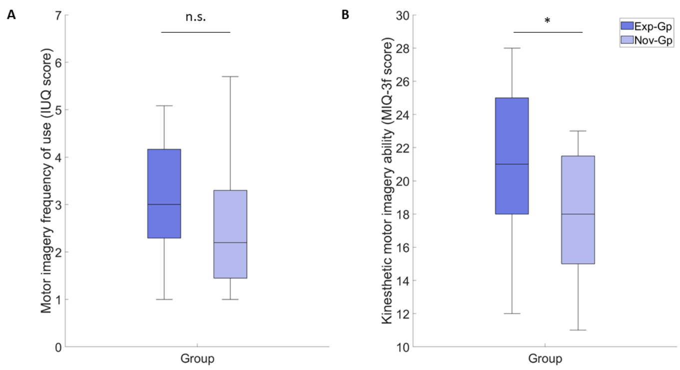

Figure 2: Box plots representing: A. The mean MI frequency of use score as a function of the group (Exp-Gp vs. Nov-Gp) B. The mean general KMI ability score as a function of the group (Exp-Gp vs. Nov-Gp)

EEG:

Finally, ANCOVA analyses (See Fig. 3) revealed a main effect of the group [(F(1,29) = 8.45, p = 0.007, $\eta^2 p$ = 0.226); Exp-Gp SMR-ERD change (M = -10.48%); Nov-Gp SMR-ERD change (M = 8.45%)] as well as a tendency towards a main effect of KMI ability [(F(1,29) = 3.03, p = 0.092, $\eta^2 p$ = 0.095)]. However they revealed no main effect of the task [(F(1,29) = 2.076, p = 0.160, $\eta^2 p$ = 0.067); FreeThrow (M = -0.215); Reaching (M = -1.816)] nor any interaction for Group x Task [(F(1,29) = 0.002, p = 0.964, $\eta^2 p$ = 0.000); Exp-Gp Task difference (M = 1.44); Nov-Gp Task difference (M = 1.75)] or Task x KMI ability (F(1,29) = 1.857, p = 0.183, $\eta^2 p$ = 0.060).

DISCUSSION

The aim of this work was to contribute to the neural efficiency debate by investigating the neurophysiological correlates of expertise during KMI. Our interest was ori-

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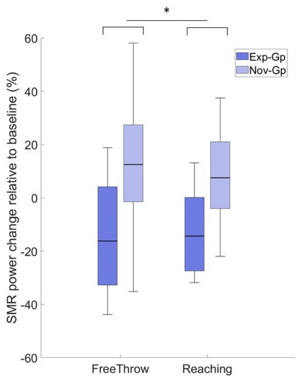

Figure 3: Box plot representing the mean SMR-ERD power as a function of the group (Exp-Gp vs Nov-Gp) and task (FreeThrow vs Reaching)

ented towards knowing if SMR-ERDs evolved with expertise and if this evolution was specific to KMI of mastered tasks. To do so, we compared experts and novices' EEG activities during a task mastered by experts only and a task that both groups mastered. For our experimental design, we chose to observe EEG activities of basketball players experts and basketball novices. The task mastered only by experts was a free throw and the non-specific task was a box reaching action.

Questionnaire results showed that while expert group did not report practicing MI more often than novice group, they self-evaluated their MI abilities higher than novices. In addition, expert group showed significantly stronger SMR-ERDs than novices during KMI whatever the task. As a matter of fact, on average, novices showed an increase of SMR power during KMI as compared to pre-trial baseline although a decrease was expected. Analyses revealed a weak effect of self-reported KMI abilities on that group effect, thus suggesting that the different neurophysiological correlates of KMI are mainly explained by expertise.

Observations of MI frequency use go against well-established findings that suggest MI use is positively linked to athletes' expertise level [25, 34]. The lack of MI use in experts could be due to the fact that half of the participants were competitors at a departmental or regional level. Although their training experience was consequent, these basketball players might not be used to engage in MI as much as higher level amateur or professional players. Indeed, Cumming and Hall, 2002 [34], showed that national athletes perceived imagery to be more relevant to improving their performance and competing effectively than recreational athletes. Therefore, a future inclusion of a third group of high expertise basketball players will allow us to see if MI practice increases with the competitive level. Moreover, to answer IUQ items, novices were asked to evaluate use of MI for all types of motor actions encountered in everyday life and activities (creative activities, skill learning...). On the other hand, basketball players were only asked about their practice of MI to enhance their basketball performance. This potentially could have induced a bias and could have artificially diminished the discrepancy between groups. Finally, the obtained score covers visual and KMI practice. Future analysis will consider items separately as the other assessed factors of this study focus on KMI only. Indeed, experts could be more familiar with KMI in general, but also in particular during mastered tasks.

Although MI frequency of use was not significantly different between groups, experts happened to have a significantly higher general KMI ability than novices. We can conclude that although practice makes perfect, a high general KMI ability does not seem to be exclusively achieved by having a quantitative MI practice. Hence, basketball expertise seems to allow athletes to develop their general KMI ability through other processes than repetition. Experts could have better MI abilities because of higher sensory mental models, either because they are used to allocating important levels of attention to kinesthetic components during execution and/or have a better ability to memorise and restore them during MI. An important limitation however persists as subjective ease of KMI use may not correlate with quality of KMI.

EEG analyses revealed that experts reached stronger SMR-ERDs than novices, whatever the task. As a matter of fact, it seems that novices increased their SMR power during KMI as compared to baseline on average, while experts decreased it. These results are aligned with many MI-BCI protocols choices to reward a greater ERD. The choice of the baseline, being the second before an MI trial, allowed to counterbalance the signal's non-stationarity. However, we suspect that this portion of recording reflects a pre-KMI state rather than a proper resting state [35]. Kornhuber and Deecke, 1965 [36], refer to this phase as the "readiness potential" and suggest that a surface negative cortical potential happens around 1s prior to movement. Additionally, it is possible that novices initiated KMI to early, which could be explained by a difficulty to voluntarily start and stop MI in an imposed timing. In which case, maximum power decrease would have happened during baseline and would have then be followed by the expected SMR-Event-Related Synchronisation (ERS) [9] during the trial, explaining the positive SMR-ERD power change in novices. It is important to have in mind that SMR-ERD precise modulation patterns during MI are still unknown. Indeed, observations of EEG signal during MI have shown very high variability between individuals [37] but also according to the number of task repetitions [38]. In a previous paper [38], authors suggested that doing MI of a short task once does not result in the same EEG patterns than continuously repeating the MI task during 4 sec. Results showed ERD and ERS components overlap in time when performing MI continuously, meaning ERD could be less detectable and more varied. Our current analysis uses the mean power values of the 10s trials. However, if trial dynamics were to be different than one single ERD per trial, this should be considered. Furthermore, experts could be able to maintain their SMR-ERD through a longer period of time than novices. Like performing MI continu-

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ously, ERD and ERS would overlap in novices and explain the SMR power increase compared to baseline. In a near future, we plan on using time-frequency analysis to observe modulations through time within and throughout trials to investigate those dynamics and their relationship with expertise. ANCOVA also provided non-significant results for the Task effect. Our initial choice was to compare two bio-mechanically close tasks. Indeed, choosing two tasks that would have had a different level of complexity as well would not have allowed us to conclude on the basketball specificity's role. Moreover, choosing tasks that mostly implied upper body segments but still involved lower body was a way of assuring us that SMR-ERD wouldn't differ strictly because of the spatially different motor and sensory representations in the Primary Motor and Sensorimotor Cortices [39]. Again, carrying time-frequency analysis throughout trials will be interesting to see if final trials reveal a more important difference between tasks. Furthermore, we found a lack of significant interaction for Task x Group indicating that SMR-ERD difference between tasks was proportionally similar for both groups. This result rejects our hypothesis that SMR-ERD is different between groups, particularly in a mastered task (FreeThrow task for experts). A possible explanation would be that experts benefit from a transfer of competences. The existence of this process has been greatly documented [40] and could be applied to KMI. Indeed, experts could have a facility to do KMI in FreeThrow task that would transfer to Reaching task, illustrated by a negative SMR-ERD change. Whereas novice group would have difficulty to produce lower SMR-ERD whatever the task. Such an interpretation was verified with KMI ability, our ANCOVA's covariable. Although this factor was not significant, it did not cancel the group effect. We can therefore conclude that there is an influence on SMR-ERD but that globally, this difference is mainly explained by expertise level.

CONCLUSION

For decades, we have associated an SMR-ERD closely followed by an ERS to MI [41], reflecting the activity of the sensorimotor cortex. We questioned ourselves on the evolution that SMR-ERD could have with expertise and what patterns we should be rewarding when using KMI-BCI to get users to enhance their performance. Currently, different theories exist. The first hypothesis, historically based, stipulates that with expertise, ability to process information increases. This translates into a sensorimotor region activation and an increased recruitment as well as an excitability of cortical neurons [9]. The second one, the neural efficiency hypothesis, goes against it as it suggests that expertise comes with a better cortical and energetic efficiency [19, 21, 22]. This would translate in a decreased activation of pertinent regions. Finally a third hypothesis, suggests that a combination of both these theories could exist [42]. Indeed, in the first stages of learning, we should reward a maximum SMR-ERD and once expertise level increases, other neurophysiological markers should be identified to reflect the optimisation of resources. Our results suggest that experts have a lower decrease of SMR-ERD compared to novices during KMI of a free throw and reaching action. Future inclusion of a higher expertise group will however be needed to provide more material concerning the mixed hypothesis.

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