

1 **Human sensorimotor cortex reactivates recent visuomotor experience**  
2 **during awake rest**

3

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23 **Abstract**

24 Previous studies have suggested that awake rest after training is helpful in improving  
25 motor performance and memory consolidation in visuomotor learning. Re-emergence of  
26 task-related activation patterns during awake rest has been reported, which play a role in  
27 memory consolidation or perceptual learning. This study aimed to test whether such  
28 reactivation occurs after visuomotor learning in the primary sensorimotor cortex. During  
29 fMRI scanning, 42 normal participants learned visuomotor tracking, while a rotational  
30 perturbation was introduced between a cursor position and a joystick angle. This  
31 visuomotor learning block was interleaved with the control block, during which the  
32 participants passively viewed a replay of previously performed cursor movements of their  
33 own. Half of the participants used their right hand, and the other half used their left hand  
34 to control the joystick. The resting-state scans were measured before and after the  
35 visuomotor learning sessions. A multivariate pattern classifier was trained to classify task  
36 and control blocks and then tested with resting scans before and after learning. Results  
37 revealed a significant increase in the number of volumes classified as the task in the post-  
38 learning rest compared with the pre-learning, indicating a re-emergence of task-related  
39 activities. Representational similarity analysis also showed a more similar pattern of  
40 activity with the task during the post-learning rest period. Furthermore, this effect is  
41 specific to the primary sensorimotor cortex contralateral to the hand used and  
42 significantly correlated with motor improvement after rest. Our finding revealed the  
43 reactivation of task-related patterns in the primary sensorimotor cortex for offline  
44 visuomotor learning.

45

46

47 **Significance Statement**

48 Previous research suggests that awake rest after learning promotes memory consolidation,  
49 which is subserved by the re-emergence of task-specific activity patterns. We aimed to  
50 determine whether such reactivation occurs in the primary sensorimotor cortex following  
51 visuomotor learning for offline memory consolidation. Our results showed a significant  
52 increase in task-classified brain volumes during the post-learning rest period compared to  
53 the pre-learning period, indicating a re-emergence of task-related activity. Furthermore,  
54 this effect was specific to the primary sensorimotor cortex contralateral to the hand used  
55 for the task and significantly correlated with the motor performance following the rest  
56 period. These findings provide evidence for the reactivation of task-related patterns  
57 during offline visuomotor learning, which may underlie memory consolidation processes.

58

59

60 **Keywords**

61 visuomotor learning; awake reactivation; fMRI multivariate pattern analysis

## 62      **Introduction**

63      Humans can flexibly acquire various motor skills through learning, and such motor  
64      memories are stored as internal models in the central nervous system (Imamizu et al.,  
65      2000; Wolpert and Ghahramani, 2000). In visuomotor learning, previous studies have  
66      suggested that sleep as well as awake rest after learning is helpful in improving behavioral  
67      performance and memory consolidation (Brashers-Krug et al., 1996; Shadmehr and  
68      Brashers-Krug, 1997; Robertson et al., 2004). For example, motor performance could be  
69      improved after a period of rest rather than immediately training a new skill, and motor  
70      memory is more consolidated and less vulnerable to interference from new motor skills  
71      (Robertson et al., 2004, 2005; Cohen et al., 2005; Press et al., 2005). It has also been  
72      reported that introducing periods of waking rest between learning sessions has a positive  
73      effect on the retention of motor memory, known as the spacing effect (Cepeda et al., 2006;  
74      Kornmeier and Sasic-Vasic, 2012; Gerbier et al., 2015). These studies suggest that the  
75      waking rest period after learning plays an essential role in the offline learning of motor  
76      memory.

77

78      The brain generates activity spontaneously, even when no specific task is required  
79      (Raichle et al., 2001; Fox and Raichle, 2007). It has been shown that spontaneous  
80      activation during rest is modulated by perceptual or motor learning (Tambini and Davachi,  
81      2019). Animal studies suggested that resting-state brain activity represents a prior  
82      distribution in visual perception, constructing an internal model of the environment  
83      (Berkes et al., 2011). Human fMRI studies have shown that the resting-state activity in  
84      the early visual cortex changes according to visual perceptual learning (Lewis et al.,  
85      2009; Guidotti et al., 2015) or enhanced resting-state functional connectivity between the

86 hippocampus and a portion of the lateral occipital complex related to memory  
87 consolidation (Tambini et al., 2010). In motor learning, human studies have reported a  
88 widespread enhanced activation of sensorimotor networks during awake rest following  
89 training with fMRI (Albert et al., 2009; Vahdat et al., 2011; Sami et al., 2014; Lin et al.,  
90 2018) or EEG (Wu et al., 2014; Gentili et al., 2015), with a link to improvement through  
91 offline learning (Gregory et al., 2014; Manuel et al., 2018).

92

93 Neural replay during rest after training is thought to be a mechanism for consolidating  
94 memory, reflecting cortical plasticity (Kurth-Nelson et al., 2023). Replay or reactivation  
95 in the hippocampus is considered an active system of memory consolidation (Klinzing et  
96 al., 2019). The first empirical evidence for this phenomenon was found by recordings of  
97 neuronal assemblies of rodents during sleep, which showed that the hippocampus exhibits  
98 autonomous reactivation of neuronal assemblies that were engaged during the previous  
99 experiential episodes (Pavlides and Winson, 1989). Subsequent studies have shown that  
100 a similar 'replay' or reactivation phenomenon occurs in the visual cortex of rodents during  
101 sleep (Ji and Wilson, 2007) as well as the awake resting period (Han et al., 2008). The  
102 autonomic reactivation lasting several minutes after repetitive visual stimulus is thought  
103 to facilitate short-term memory and contribute to long-term perceptual learning (Han et  
104 al., 2008). However, it remains to be elucidated whether there are reactivations of neural  
105 populations related to learned sensorimotor skills, together with the relationship to offline  
106 improvement in behavioral performance.

107

108 This study aimed to test whether such re-emergence of activation occurs after visuomotor  
109 learning in the human sensorimotor cortex. In our experiments, the participants performed

110 continuous manual visuomotor tracking within an MRI scanner, and we measured brain  
111 activations with fMRI during both the learning period and the rest period before and after  
112 the learning. Using a multi-voxel pattern analysis (MVPA), we first tried to test whether  
113 brain activity patterns are similar to those during the previous motor task (reactivation) in  
114 the resting period. Furthermore, we tested whether such reactivation has a facilitatory  
115 effect on behavioral performance after learning.

116

117 **Materials and Methods**

118 **Participants**

119 Participants included 42 volunteers (29 males and 13 females) with a mean age of 22.7  
120 years (range, 20–34 years). Sample size was determined before data collection based on  
121 our previous study, which used MVPA with the two groups of participants to compare  
122 the neural representation of the primary sensorimotor cortex (Ogawa et al., 2019). Half  
123 of the participants ( $n = 21$ , 6 female) used their right hand, and the other half ( $n = 21$ , 7  
124 female) used their left hand to control the joystick in the MRI scanner. One participant  
125 (male) of the left-hand group was excluded from the analysis because he did not move  
126 the cursor frequently during the task period. All participants were right-handed, as  
127 assessed by a modified version of the Edinburgh Handedness Inventory (Oldfield, 1971)  
128 modified for Japanese participants (Hatta and Nakatsuka, 1975). Written informed  
129 consent was obtained from all participants in accordance with the Declaration of Helsinki.  
130 The experimental protocol received approval from the local ethics committee.

131

132 **Task procedures**

133 The participants underwent the fMRI scanning, which consisted of 4 task sessions and 2  
134 resting-state (RS) scanning sessions before (pre-RS) and after (post-RS) the first 3 task  
135 sessions (Figure 1A). In the task sessions, the participants performed continuous  
136 visuomotor tracking movement (Ogawa and Imamizu, 2013), while a rotational  
137 perturbation of 30° was introduced between a cursor position and a joystick angle. In the  
138 visuomotor learning block (task block, 12 s), the participants were instructed to chase a  
139 randomly moving target in the frame by controlling the cursor with the joystick. This  
140 visuomotor learning block was interleaved with the replay block (12 s), during which the

141 participants passively viewed a replay of previously performed cursor movements of their  
142 own. The task session consisted of 10 task blocks and 10 replay blocks. In the RS sessions,  
143 participants were asked to stare at the cross in the center, not to move their bodies, not to  
144 sleep, and to remain rested. Each RS session lasted 6 minutes (Figure 1B). Finally, the  
145 participants underwent a T1 anatomical scanning.

146

147 ----- FIGURE 1 ABOUT HERE -----

148

149 **MRI acquisition**

150 All scans were performed on a Siemens (Erlangen, Germany) 3-Tesla Prisma scanner  
151 with a 64-channel head coil at Hokkaido University. T2\*-weighted echo-planar imaging  
152 (EPI) was used to acquire a total of 174 scans per task session and 122 scans per rest  
153 session, with a gradient EPI sequence. The first three scans within each session were  
154 discarded to allow for T1 equilibration. The scanning parameters were repetition time  
155 (TR), 3000 ms; echo time (TE), 30 ms; flip angle (FA), 90°; field of view (FOV), 192 ×  
156 192 mm; matrix, 94 × 94; 36 axial slices; and slice thickness, 3.0 mm with a 0.75 mm  
157 gap. T1-weighted anatomical imaging with an MP-RAGE sequence was performed using  
158 the following parameters: TR, 2300 ms; TE, 2.41 ms; FA, 8°; FOV; 256 × 256 mm; matrix,  
159 256 × 256; 224 axial slices; and slice thickness, 0.8 mm without a gap.

160

161 **fMRI mass-univariate analysis**

162 Image preprocessing was performed using the SPM12 software (Welcome Department of  
163 Cognitive Neurology, <http://www.fil.ion.ucl.ac.uk/spm>). All functional images were

164 initially realigned to adjust for motion-related artifacts. Volume-based realignment was  
165 performed by co-registering images using rigid body transformation to minimize the  
166 squared differences between volumes. The realigned images were then spatially  
167 normalized with the Montreal Neurological Institute template based on the affine and  
168 nonlinear registration of coregistered T1-weighted anatomical images (normalization  
169 procedure of SPM). They were resampled into 3-mm-cube voxels with the sinc  
170 interpolation. Images were spatially smoothed using a Gaussian kernel of  $6 \times 6 \times 6$  mm  
171 full width at half-maximum. However, images used for MVPA were not smoothed to  
172 avoid blurring the fine-grained information contained in the multivoxel activity (Mur et  
173 al., 2009; Kamitani and Sawahata, 2010). We analyzed significantly activated areas  
174 during the task block compared with the replay (observation only) block with the mass  
175 univoxel analysis. Activation was the threshold at  $p < .05$  corrected for multiple  
176 comparisons for a family-wise error (FWE), with an extent threshold of 15 voxels.

177

## 178 **MVPA**

179 We used MVPA to classify the task and replay activities using a spatiotemporal decoder  
180 (Guidotti et al., 2015). The classifier was based on a linear support vector machine run  
181 by LIBSVM (<http://www.csie.ntu.edu.tw/~cjlin/libsvm>) with a fixed regularization  
182 parameter  $C = 1$ . The region of interest (ROI) was defined anatomically with the  
183 precentral and postcentral cortices of the automated anatomical labeling (AAL) toolbox  
184 (Tzourio-Mazoyer et al., 2002) as the primary sensorimotor cortex. First, we tried to  
185 classify the brain activities of the task block and those of the replay block with leave one-  
186 session out cross-validation among the first 3 task sessions. The activation pattern during  
187 the task block and those during the replay block with 4 consecutive volumes in the 3 task

188 sessions were used as the spatio-temporal patterns to train the decoder (Figure 1B middle).  
189 This analysis produced the mean classification accuracy among the 3 task sessions using  
190 leave one-session-out cross-validation. Next, we investigated whether the reappearance  
191 of task-related activation patterns occurred in the primary sensorimotor cortex more  
192 frequently after task training (post-RS) than before the task period (pre-RS). As in the  
193 above analysis of the task sessions, the decoder was first trained to classify the brain  
194 activities between the task block and the replay blocks using the 3 task sessions as the  
195 training data. This decoder was then tested with the activities of the pre-RS and post-RS  
196 to see whether a task-like brain activity pattern occurred during the rest session (Figure  
197 1B bottom). This analysis used a sliding time window, where a window the length of the  
198 task or replay block (4 volumes) was slid through the resting scan volumes, advancing  
199 one volume per analysis.

200

201 Pattern similarity-based classification was also conducted using representational  
202 similarity analysis (RSA) (Kriegeskorte et al., 2008). We calculated the Euclidean  
203 distance between brain activation patterns during pre- and post-rest and task/non-task  
204 patterns. If the task pattern was close to the sample in the test dataset, this data was  
205 classified as a task pattern; otherwise, it was classified as a non-task (observation of  
206 replay) pattern.

207

208 **Results**

209 **Behavioral results**

210 We conducted a mixed-effects analysis of variance (ANOVA) on the average tracking  
211 error between the right-hand and left-hand groups during the four task sessions. The  
212 results showed a significant main effect of the groups ( $F(1, 39) = 7.65, p = .01, \eta_p^2 = .16$ )  
213 and of the sessions ( $F(3, 117) = 17.19, p < .001, \eta_p^2 = .31$ ) with no significant interaction  
214 ( $F(3, 117) = 1.16, p = .33, \eta_p^2 = .03$ ). Post-hoc comparisons showed a significantly larger  
215 tracking error in task session 1 compared with session 2 ( $t(40) = 4.46, p_{Bonf} < .001$ ),  
216 session 3 ( $t(40) = 4.75, p_{Bonf} < .001$ ) and session 4 ( $t(40) = 7.01, p_{Bonf} < .001$ ) with a  
217 marginally significant difference between session 2 and 4 ( $t(40) = 2.55, p_{Bonf} < .1$ ) (Figure  
218 2).

219

220 **fMRI mass-univariate analysis**

221 We analyzed the activated regions of the brain using the conventional mass-univariate  
222 analysis of single voxels for each group. We compared the activities between the task  
223 blocks and replay blocks within four task sessions to reveal the brain regions activated  
224 during the task block. We then found the activations mainly in the primary sensorimotor  
225 cortex and the cerebellum, which are either contralateral or ipsilateral to the hand used,  
226 together with the small clusters in the thalamus, the basal ganglia, and the central  
227 operculum (Figure 3; Table 1).

228

229 ----- FIGURE 2, TABLE 1 ABOUT HERE -----

230

231 **MVPA**

232 We first classified the brain activities of the task block and those of the replay  
233 (observation only) block with leave one-session out cross-validation among the first 3  
234 task sessions. A mixed-effects ANOVA was conducted on the classification accuracy in  
235 the precentral and postcentral cortex with the hemisphere (left/right) as a within-subject  
236 factor and the group (left-handed/right-handed) as a between-subject factor. The  
237 precentral cortex showed a significant interaction ( $F(1, 39) = 22.07, p < .001, \eta_p^2 = .36$ )  
238 with no significant main effect of the group ( $F(1, 39) = 0.06, p = .81, \eta_p^2 = .002$ ) and the  
239 hemisphere ( $F(1, 39) = 1.01, p = .32, \eta_p^2 = .025$ ). Post-hoc analysis showed a significantly  
240 higher classification accuracy in the contralateral hemisphere for both the right-hand  
241 ( $t(20) = 4.46, p < .001$ , Cohen's d = 1.00) and the left-hand group ( $t(19) = -2.36, p = .03$ ,  
242 Cohen's d = 0.55). The postcentral cortex also showed a significant interaction ( $F(1, 39) = 19.07, p < .001, \eta_p^2 = .328$ ) with no significant main effect of the group ( $F(1, 39) = 0.21, p = .65, \eta_p^2 = .005$ ) and the hemisphere ( $F(1, 39) = 0.007, p = .93, \eta_p^2 = .0002$ ). Post-hoc  
245 analysis showed a significantly higher classification accuracy in the contralateral  
246 hemisphere for both the right-hand group ( $t(20) = 3.41, p = .003$ , Cohen's d = 0.73) and  
247 the left-hand group ( $t(19) = -2.81, p = .01$ , Cohen's d = 0.64). These results thus showed  
248 successful classification of the task vs. non-task patterns, together with significantly  
249 higher accuracy in the contralateral sensorimotor cortex compared to the ipsilateral side  
250 of the hand used (Figure 4).

251

252 ----- FIGURE 4 ABOUT HERE -----

253

254 Next, we investigated whether the re-emergence of task-related activation patterns  
255 occurred more frequently after task training (post-RS) than before the task period (pre-

256 RS). As in the previous analysis, the decoder was first trained to classify the brain  
257 activities between the task and the non-task patterns using all the 3 task sessions, and this  
258 decoder was tested with the activities of the pre- and post-RS to see whether a task-like  
259 brain activity pattern occurred during the resting-state session. A mixed-effects ANOVA  
260 was conducted on the frequency of occurrence of the volumes labeled as task patterns  
261 during pre-task and post-task resting-state sessions (pre-/post-RS) as a within-subject  
262 factor and the group (right-hand/left-hand) as a between-subject factor. The left precentral  
263 cortex showed a significant main effect of both the session ( $F(1, 39) = 4.52, p = .039, \eta_p^2$   
264 = .10) and the group ( $F(1, 39) = 17.24, p < .001, \eta_p^2 = .31$ ) with a non-significant  
265 interaction ( $F(1, 39) = 1.78, p = .19, \eta_p^2 = .04$ ). This significant effect of the group without  
266 significant interaction suggests that the similar pattern of task activation was not only  
267 present in the post-RS but already in the pre-RS. The right precentral cortex showed a  
268 marginally significant main effect of the group ( $F(1, 39) = 4.02, p = .052, \eta_p^2 = .094$ ) with  
269 non-significant main effect of the session ( $F(1, 39) = 1.94, p = .17, \eta_p^2 = .047$ ) and a  
270 marginally significant interaction ( $F(1, 39) = 2.88, p = .10, \eta_p^2 = .069$ ). The left  
271 postcentral cortex showed a significant main effect of both the group ( $F(1, 39) = 5.61, p$   
272 = .023,  $\eta_p^2 = .13$ ) and the session ( $F(1, 39) = 8.95, p = .005, \eta_p^2 = .19$ ) with a significant  
273 interaction ( $F(1, 39) = 4.64, p = .04, \eta_p^2 = .11$ ). The right postcentral cortex showed no  
274 significant main effect of both the group ( $F(1, 39) < .001, p = 1.00, \eta_p^2 < .001$ ) and the  
275 session ( $F(1, 39) = 2.63, p = .11, \eta_p^2 = .06$ ) with no significant interaction ( $F(1, 39) =$   
276  $2.12, p = .15, \eta_p^2 = .05$ ) (Figure 5).

277

278 ----- FIGURE 5 ABOUT HERE -----

279

280 To directly compare differences in classification accuracy between pre- and post-task for  
281 each hemisphere and group, we subtracted the classification accuracy of pre-RS from  
282 post-RS using the same results. The precentral cortex showed a significant interaction  
283 ( $F(1, 39) = 5.93, p = .02, \eta_p^2 = .12$ ) with a non-significant main effect of both the groups  
284 ( $F(1, 39) = 0.07, p = .80, \eta_p^2 < .001$ ) and the hemisphere ( $F(1, 39) = .30, p = .59, \eta_p^2$   
285 = .008). Post-hoc analysis showed larger numbers of task-labeled volumes in the  
286 contralateral hemisphere for both groups, and this difference is significant in the right-  
287 hand group ( $t(20) = 2.26, p = .04$ , Cohen's d = 0.51) but not in the left-hand group ( $t(19)$   
288 = -1.22,  $p = .24$ , Cohen's d = 0.28). The postcentral cortex showed a significant interaction  
289 ( $F(1, 39) = 8.79, p = .001, \eta_p^2 = .18$ ) with no significant main effect of the group ( $F(1,$   
290  $39) = 0.02, p = .90 \eta_p^2 < .001$ ) and the hemisphere ( $F(1, 39) = 0.40, p = .53, \eta_p^2 = .01$ ).  
291 Post-hoc analysis showed significantly or marginally significantly larger numbers of task-  
292 labeled volumes in the contralateral hemisphere for both the right-hand group ( $t(20) =$   
293 2.28,  $p = .03$ , Cohen's d = 0.51) and the left-hand group ( $t(19) = -1.94, p = .07$ , Cohen's  
294 d = 0.44). Our results thus showed a higher frequency of reactivations in the primary  
295 sensorimotor cortex during the post-learning compared to the pre-learning period, and  
296 that this effect is specific to the primary sensorimotor cortex contralateral to the hand used  
297 (Figure 6A).

298

299 We further conducted the same analysis with the RSA results. The precentral cortex  
300 showed a significant interaction ( $F(1, 39) = 10.23, p = .003, \eta_p^2 = .21$ ) with no significant  
301 main effect of both the group ( $F(1, 39) = 0.01, p = .91, \eta_p^2 < .001$ ) and the hemisphere  
302 ( $F(1, 39) = .23, p = .63, \eta_p^2 = .005$ ). Post-hoc analysis showed significantly or marginally  
303 significantly larger numbers of task-labeled volumes in the contralateral hemisphere for

304 both the right-hand group ( $(t(20) = 1.75, p = .10$ , Cohen's  $d = 0.39$ ) and the left-hand  
305 group ( $(t(19) = -3.00, p = .008$ , Cohen's  $d = 0.68$ ). The postcentral cortex also showed a  
306 significant interaction ( $F(1, 39) = 11.86, p = .001, \eta_p^2 = .23$ ) with no significant main  
307 effect of the group ( $F(1, 39) = 0.31, p = .58, \eta_p^2 = .008$ ) and the hemisphere ( $F(1, 39) =$   
308  $0.07, p = .80, \eta_p^2 = .002$ ). Post-hoc analysis showed significantly larger numbers of task-  
309 labeled volumes in the contralateral hemisphere for both the right-hand group ( $(t(20) =$   
310  $2.37, p = .03$ , Cohen's  $d = 0.53$ ) and the left-hand group ( $(t(19) = -2.59, p = .02$ , Cohen's  
311  $d = 0.59$ ). These results are consistent with the previous classification analysis, regarding  
312 the higher frequency of reactivations during the post-learning in the primary sensorimotor  
313 cortex contralateral to the hand used (Figure 6B).

314

315 ----- FIGURE 6 ABOUT HERE -----

316

317 Finally, we investigated the relationship between the frequency of reactivation during the  
318 rest and behavioral performance. We thus analyzed the correlation between the increase  
319 in the percentage of labeled task patterns from pre-RS to post-RS in the contralateral  
320 hemisphere of each group and the decrease in tracking errors from the average of the first  
321 3 task sessions to the last task session. The results of the right-hand group showed a  
322 significant correlation in the left postcentral cortex ( $R = .64, p_{Bonf} < .05$ : Figure 7C), but  
323 no significant correlation in the left precentral cortex ( $R = -.04, p_{Bonf} > .05$ : Figure 7A).  
324 For the left-hand group, no significant correlation was found in either the right precentral  
325 ( $R = -.14, p_{Bonf} > .05$ : Figure 7B) or the postcentral cortex ( $R = -.48, p_{Bonf} > .05$ : Figure  
326 7D).

327

328

----- FIGURE 7 ABOUT HERE -----

329

330 **Discussion**

331 In this study, we used fMRI with MVPA to reveal the re-emergence of task-related  
332 activation patterns in the resting state after the visuomotor learning task. We first  
333 classified the brain activities of the task and those of the replay (observation only) using  
334 the first 3 task sessions, which showed successful classification with significantly higher  
335 accuracy in the contralateral sensorimotor cortex compared to the ipsilateral side of the  
336 hand used. Next, we investigated whether the reappearance of task-related activation  
337 patterns occurred more frequently after task training (post-RS) than before the task period  
338 (pre-RS). Both multivariate classification and RSA consistently revealed a significantly  
339 higher number of reactivations in the primary sensorimotor cortex during the post-  
340 learning period compared to the pre-learning period. Furthermore, this effect is specific  
341 to the primary sensorimotor cortex contralateral to the hand used and is significantly  
342 correlated with motor performance after rest. Our findings reveal the reactivation of task-  
343 related patterns in the primary sensorimotor cortex during offline visuomotor learning.

344

345 A number of previous studies using spatial navigation tasks in rodents have shown that  
346 patterns of neural activity associated with spatial experience are replayed in the  
347 hippocampus during rest, which is related to memory consolidation (Euston et al., 2007;  
348 Carr et al., 2011; Grosmark and Buzsáki, 2016). In addition to spatial navigation tasks,  
349 motor learning also induces replay-like activations after rodents learn a skilled upper-  
350 limb task, which is related to offline improvements in motor performance (Gulati et al.,  
351 2014; Ramanathan et al., 2015). A recent human study with magnetoencephalography  
352 (MEG) also revealed fast waking neural replay during the same rest periods in which  
353 rapid consolidation occurs across the hippocampus and neocortex after learning of novel

354 motor sequence (Buch et al., 2021). A human fMRI study reported that the multi-voxel  
355 pattern in resting-state brain activity corresponds to either wrist or finger movements in  
356 the motor-related areas of each hemisphere of the cerebrum and cerebellum (Kusano et  
357 al., 2021), which could possibly be acquired through prior experience of bodily movements.  
358 Another human fMRI study also reported a replay activity in the hippocampus during  
359 wakeful rest after decision-making with non-spatial sequences (Schuck and Niv, 2019),  
360 which indicates that reactivation is a more domain-general process, not limited to specific  
361 cognitive functions.

362

363 A recent invasive brain recording study measured the activity of intracortical  
364 microelectrode arrays in the left anterior tegmental gyrus while the participants were  
365 completing a novel motor task and a subsequent night's sleep to determine whether replay  
366 occurs after motor learning (Rubin et al., 2022). They found that neural signals recorded  
367 overnight replayed the target sequences in the memory game at a significantly higher  
368 frequency than chance. Another human intracranial recording study also revealed a replay  
369 of activity for a learned motor sequence during awake rest in the motor cortex with a  
370 comparable rate of replay event (Eichenlaub et al., 2020). These invasive brain recording  
371 studies indicate an offline replay of neural firing patterns that underlie the waking  
372 experience and play a role in memory consolidation.

373

374 A previous study using non-invasive brain stimulation showed that when the primary  
375 motor cortex is disrupted by the transcranial magnetic stimulation (TMS) following motor  
376 learning, there is a reduction in learning, and this effect is specific to the waking rest  
377 period and is not observed during sleep (Robertson et al., 2005). Another TMS study also

378 showed disrupting the primary motor cortex impairs early boost but not delayed gains in  
379 performance in motor sequence learning (Hotermans et al., 2008). These previous brain  
380 stimulation studies indicate the roles of the primary motor cortex for offline learning of  
381 visuomotor control.

382

383 Regarding the relationship between reactivation and behavior, we found a significant  
384 correlation between the frequency of reactivation patterns and the decrease in tracking  
385 errors from pre- to post-learning in the left postcentral cortex (Figure 7C), but not in the  
386 precentral cortex (Figure 7A), for the right-hand group. This finding that reactivation in  
387 the primary somatosensory cortex correlates with behavioral performance may suggest  
388 that reactivation at the sensory level, rather than the motor level, is more important for  
389 later performance improvement. In contrast, we found no significant correlation in both  
390 the precentral and postcentral cortex for the left-hand group (Figure 7B & D). As all of  
391 the participants are right-handed, this effect might be dependent on the handedness. The  
392 left-hand group also showed a non-significant or marginally significant increase in the  
393 task-like volumes during post-RS compared with pre-RS in the precentral and postcentral  
394 cortex, respectively (Figure 6A). As the left-hand group showed significantly more  
395 tracking errors compared with the right-hand group (Figure 2), insufficient learning with  
396 the non-dominant hand may have affected the less clear effects of the left-hand group,  
397 which need further investigation.

398

399 The present experiment showed that the contralateral sensorimotor cortex resembles task  
400 activity compared to the ipsilateral side, not only in the post-learning but also in the pre-  
401 learning resting period. The fact that this task-like activity was already present before the

402 task is somewhat puzzling, but this may be related to the "pre-play" reported in the  
403 spontaneous activity of rodents. Pre-play, as opposed to replay, is a phenomenon in which  
404 hippocampal neurons are activated sequentially according to the place fields when rodents  
405 perform a spatial navigation task, but this occurs during rest before the animal actually  
406 performs the task (Dragoi and Tonegawa, 2011, 2013). This phenomenon suggests that  
407 hippocampal activation during rest may function not only in memory consolidation and  
408 retrieval but also in the planning stage. A recent human fMRI study also reported preplay-  
409 like activations for the acquisition of new semantic knowledge (Kurashige et al., 2018).  
410 Considering these previous studies, the current finding may also reflect preplay-like  
411 activations for learning visuomotor skills, which should be investigated in the future.

412

413 The current study has some limitations. Firstly, the increased activity pattern similar to  
414 the task during the post-learning resting period may simply reflect residual brain activity  
415 after performing the motor task. We consider this possibility unlikely for the following  
416 reasons. We displayed the frequency of labels that were classified as the task for the  
417 classification analysis and the RSA during the resting periods (Supplementary Figure 1).  
418 If the observed effect reflects simply residual brain activity after a motor task, we should  
419 see more task-like activity patterns immediately after the task is completed. Instead, the  
420 results showed that the task-assigned labels were distributed throughout the 6-minute  
421 resting period. This suggests that this is not residual task-related activity, but rather  
422 sustained brain activity during the resting state. Secondly, related to the previous point,  
423 the observed reactivation may reflect that the subjects were intentionally or  
424 unintentionally rehearsing the previous motor learning experience at rest even though the  
425 subjects were asked to remain rested (see Methods). We consider this possibility unlikely,

426 because also in this case, the residual effects of the motor memory should gradually  
427 diminish over time. As was shown above, the task-like volume did not decrease over time,  
428 so we thus consider it unlikely that the observed reactivation was a rehearsal of motor  
429 memory. However, further experiments, such as imposing different kinds of cognitively  
430 demanding tasks to prevent such rehearsal at rest, will be needed in the future to clearly  
431 reject this possibility. Thirdly, the present study deals only with one rotational  
432 transformation and not with brain activity specific to a particular transformation rule. Our  
433 previous study has shown that multiple rotational transformations are acquired in the  
434 primary sensorimotor cortex (Ogawa and Imamizu, 2013), and the relevance of specific  
435 motor skills to the reproduction of brain activity patterns is unclear in the present  
436 experiment. Lastly, the present experiment only deals with kinematic motor adaptation  
437 with a rotational transformation, and it is not clear whether the results can be generalized  
438 to other motor adaptations and learning tasks, including sequential motor learning (e.g.,  
439 serial reaction time task; SRTT) (Robertson, 2007). This should also be investigated in  
440 future studies.

441

442 In summary, we found a significant increase in task-related activities in the post-learning  
443 period compared with the pre-learning period. In addition, this effect is specific to the  
444 primary sensorimotor cortex contralateral to the hand used and significantly correlated  
445 with motor improvement after rest. Our finding revealed the reactivation of task-related  
446 patterns in the primary sensorimotor cortex for visuomotor learning.

447

448 **Tables**

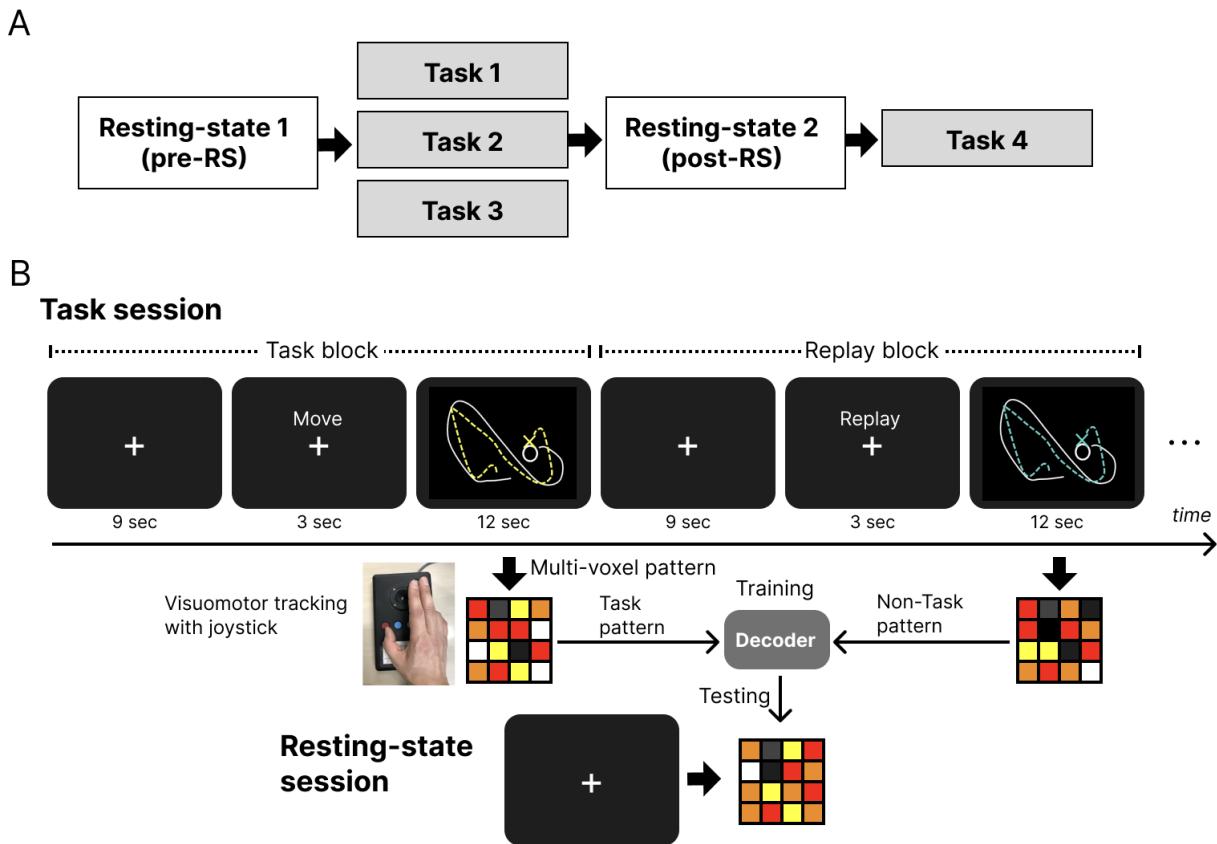
449 Table 1: Anatomical regions, peak voxel coordinates, and t-values of observed activation  
450 during task compared with replay blocks for each group.

Anatomic region	voxels	MNI coordinates			t-value
		x	y	z	
<i>Right-hand group</i>					
R cerebellum	673	21	-49	-22	20.45
L precentral/postcentral gyrus	713	-30	-25	56	16.09
L thalamus	55	-12	-19	5	11.47
L cerebellum	63	-30	-58	-25	5.62
<i>Left-hand group</i>					
L cerebellum	400	-18	-52	-22	16.35
R precentral/postcentral gyrus	845	36	-13	59	15.39
R thalamus	55	12	-19	5	15.08
L cerebellum	62	-21	-58	-46	12.43
R basal ganglia	38	21	-7	-1	5.94
R central operculum	22	42	-1	14	9.66
R cerebellum	15	30	-55	-22	5.30

451 Activation was reported with a threshold of  $p < 0.05$  corrected for family-wise error  
452 (FWE) with an extent threshold of 15 voxels. MNI, Montreal Neurological Institute; L,  
453 left hemisphere; R, right hemisphere.

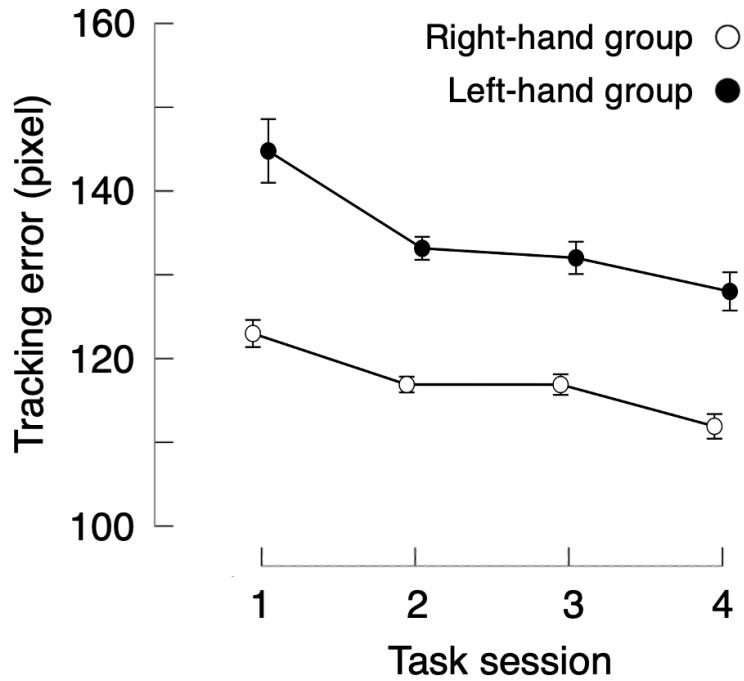
454

455 Figures



456  
457 Figure 1: Schematic description of experimental time-course and multi-voxel  
458 pattern analysis (MVPA)

459 A) Experimental schedule of the task and resting-scan sessions. B) The upper part shows  
460 the example time-course for one trial consisting of 1 task block and 1 replay block within  
461 the task session. The lower part shows the activity patterns during the task and replay  
462 blocks within the task sessions, which are used as task and non-task patterns for training  
463 of the decoder. The task and non-task patterns in 3 task sessions are used to train the  
464 decoder and then tested the pre-RS and post-RS activities.

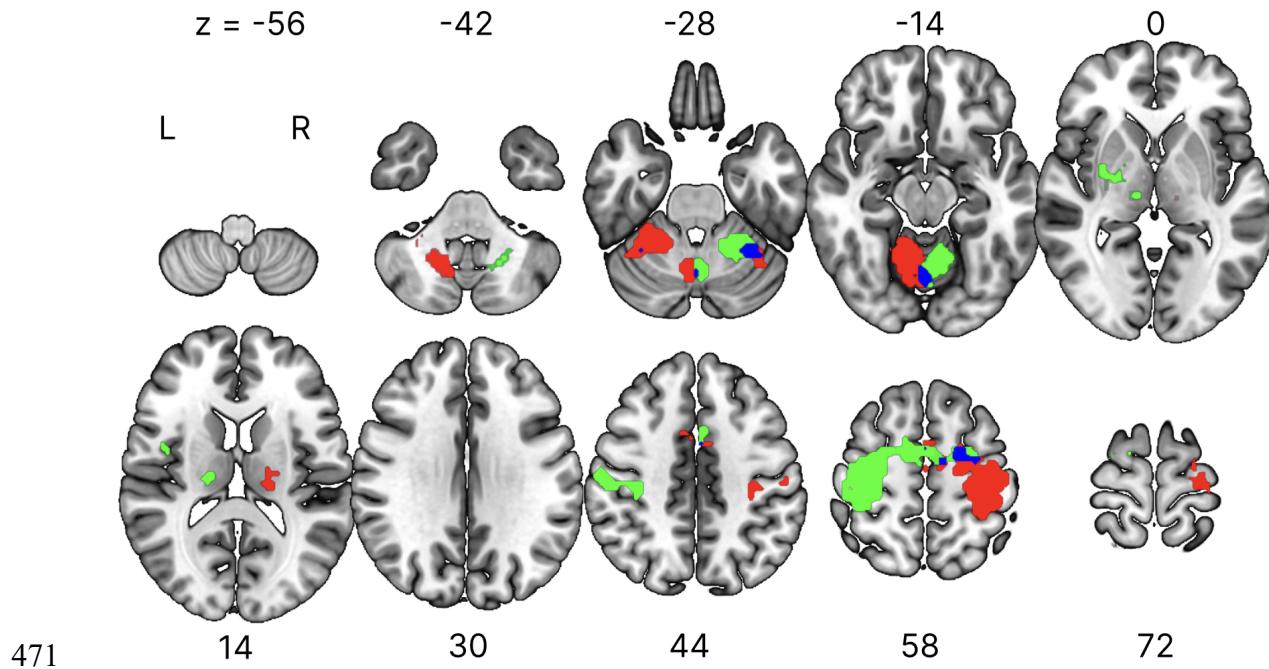


465

466 **Figure 2: Behavioral results of tracking error**

467 The average tracking error between the target and the cursor (in pixels) during the task  
468 sessions for the right-hand group (white dots) and the left-hand group (black dots). The  
469 error bars show SEMs.

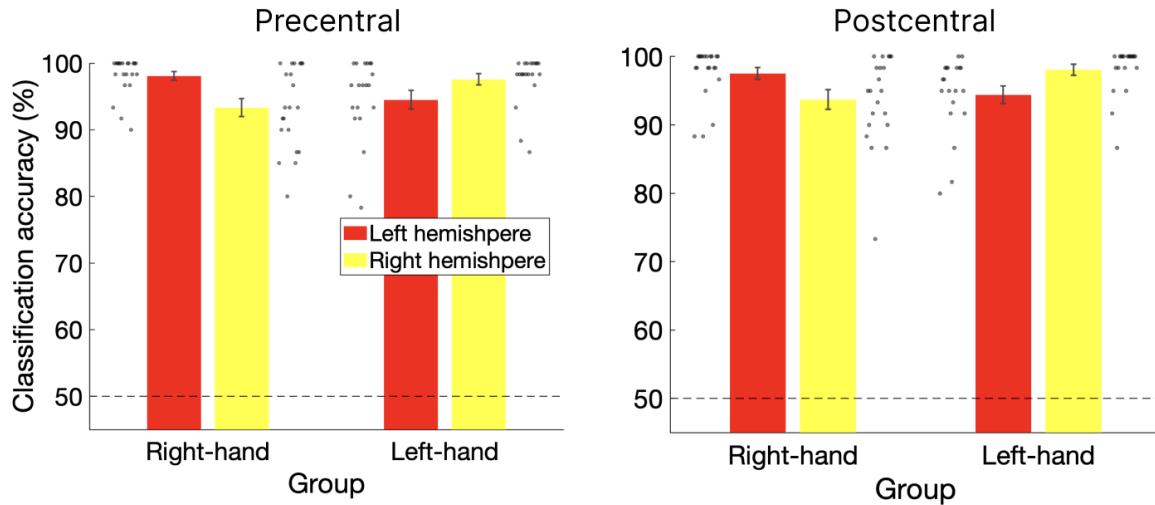
470



472 **Figure 3: Activated areas during the task block with the mass-univariate analysis**

473 Areas activated during the task block compared with the replay block in task sessions for  
474 the right-hand group (green) and the left-hand group (red) with their overlap (blue).  
475 Activation was reported with a threshold of  $p < .05$  corrected for multiple comparisons  
476 for family-wise error (FWE) with an extent threshold of 15 voxels. MNI coordinates of  
477 activated foci are reported in Table 1. The regions are displayed in the horizontal plane  
478 with Z denoting locations in the MNI coordinates. L, left hemisphere; R, right hemisphere.

479

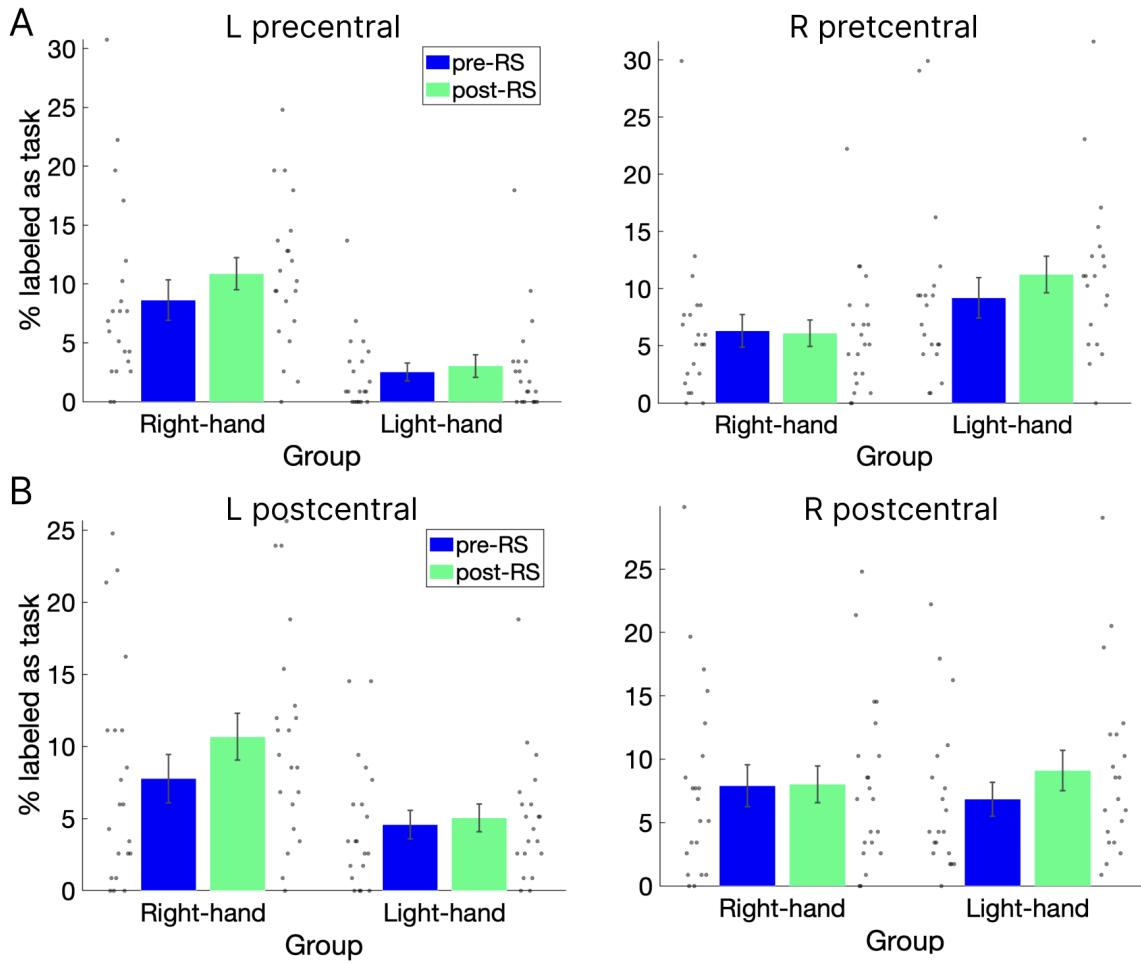


480

481 **Figure 4: Results of the task and replay classification among task sessions**

482 The classification accuracy of task and replay (observation only) block activities among  
483 3 task sessions in the precentral cortex (left) and postcentral cortex (right) for each group.  
484 The red and yellow bars showed the left and right hemispheres, respectively. The gray  
485 dots show the individual data. The black dotted lines denote the chance level of the  
486 classification. Error bars denote SEMs.

487

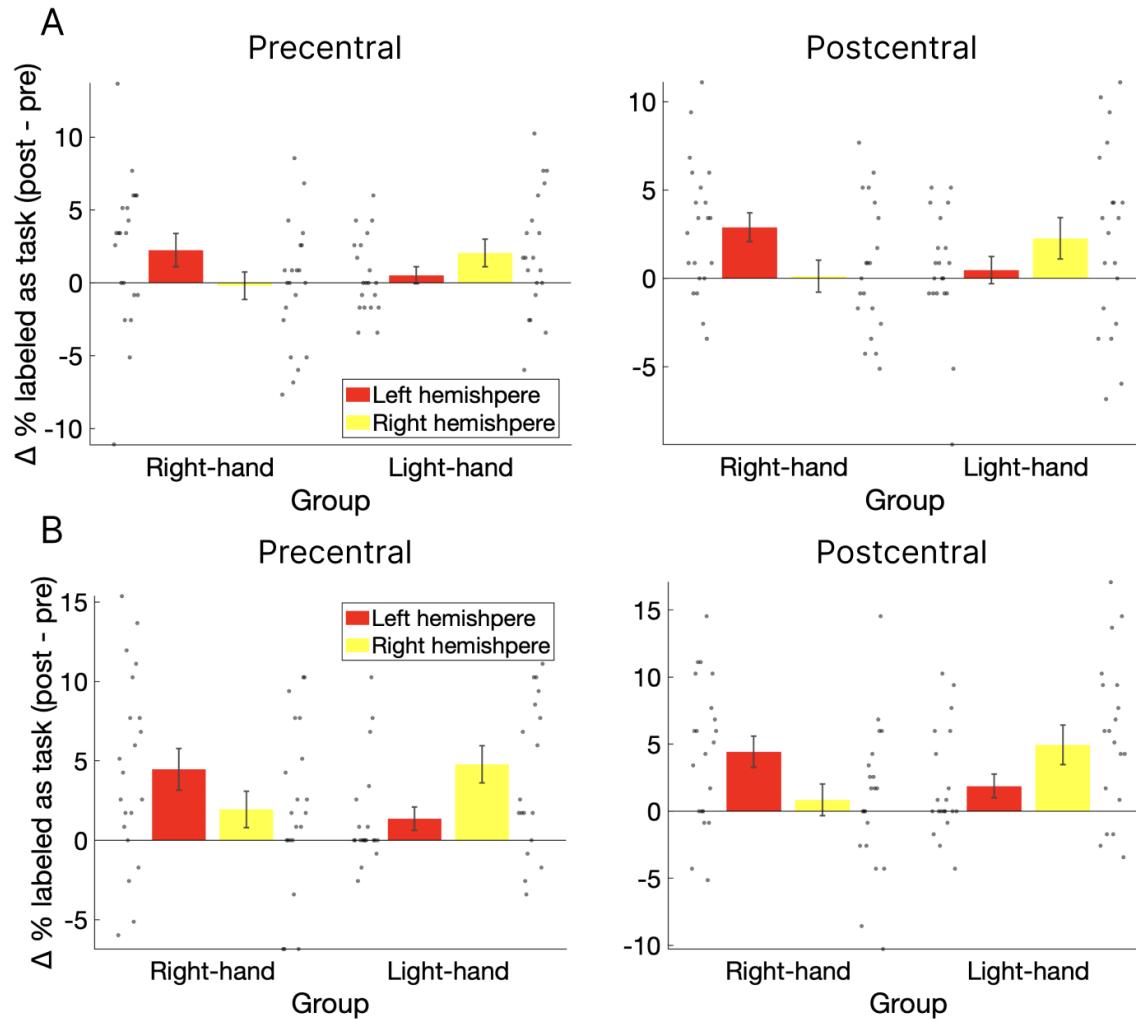


488

489 **Figure 5: Percentage of the volumes labeled as task pattern during rest sessions**

490 Percentage of the volumes in the precentral (A) and the postcentral cortex (B) classified  
491 as the task pattern compared with the non-task (observation only) pattern during the pre-  
492 RS (blue) and post-RS (green) for each group. The gray dots show the individual data. L,  
493 left hemisphere; R, right hemisphere. Error bars denote SEMs.

494



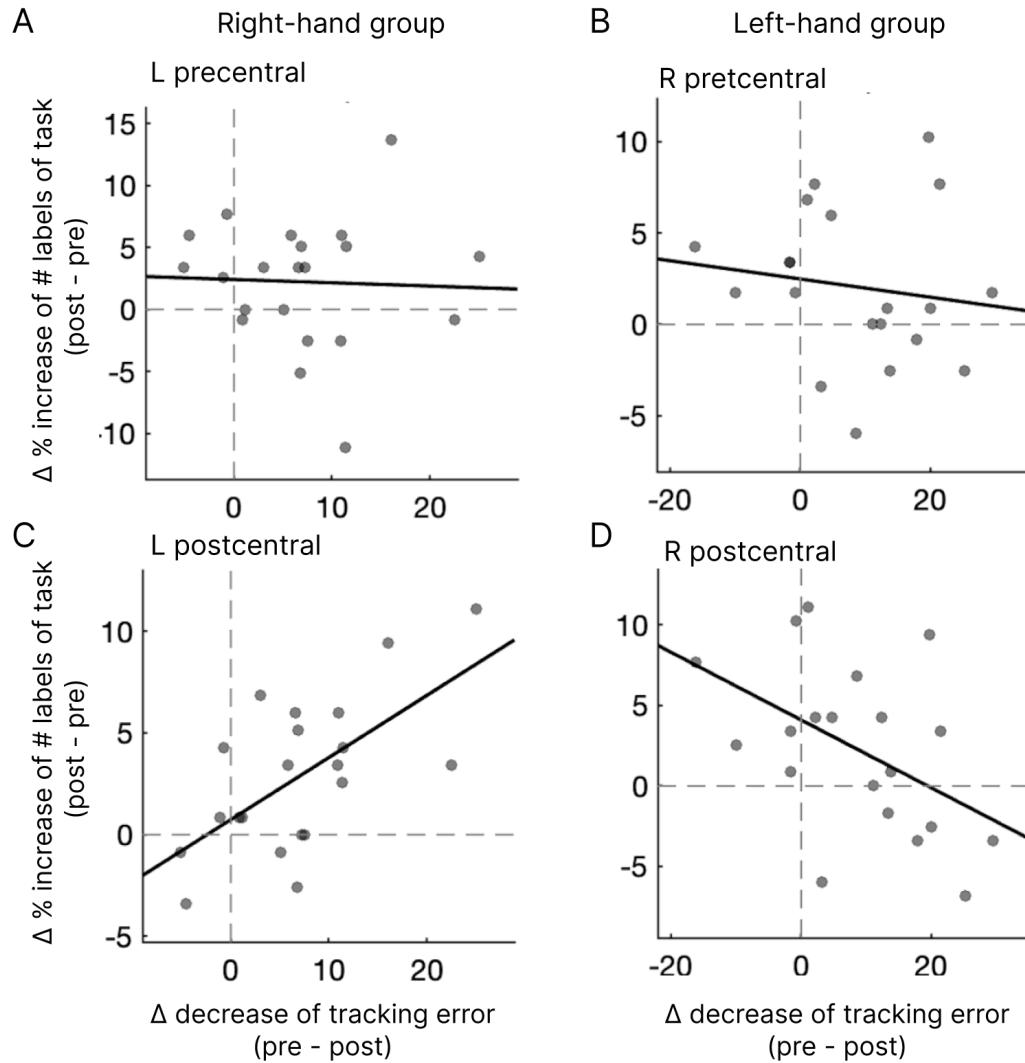
495

496 **Figure 6: Difference in the frequency of the volumes labeled as the task in pre-RS**  
497 **and post-RS**

498 The difference in frequency between pre-RS and post-RS volumes labeled as (A) or more  
499 similar to (B) the task pattern compared with the non-task (observation only) pattern in  
500 the precentral and the postcentral cortex with the classification analysis (A) and the RSA  
501 (B). The red and yellow bars show the left and right hemispheres, respectively. The gray  
502 dots show the individual data. Error bars denote SEMs.

503

504



505

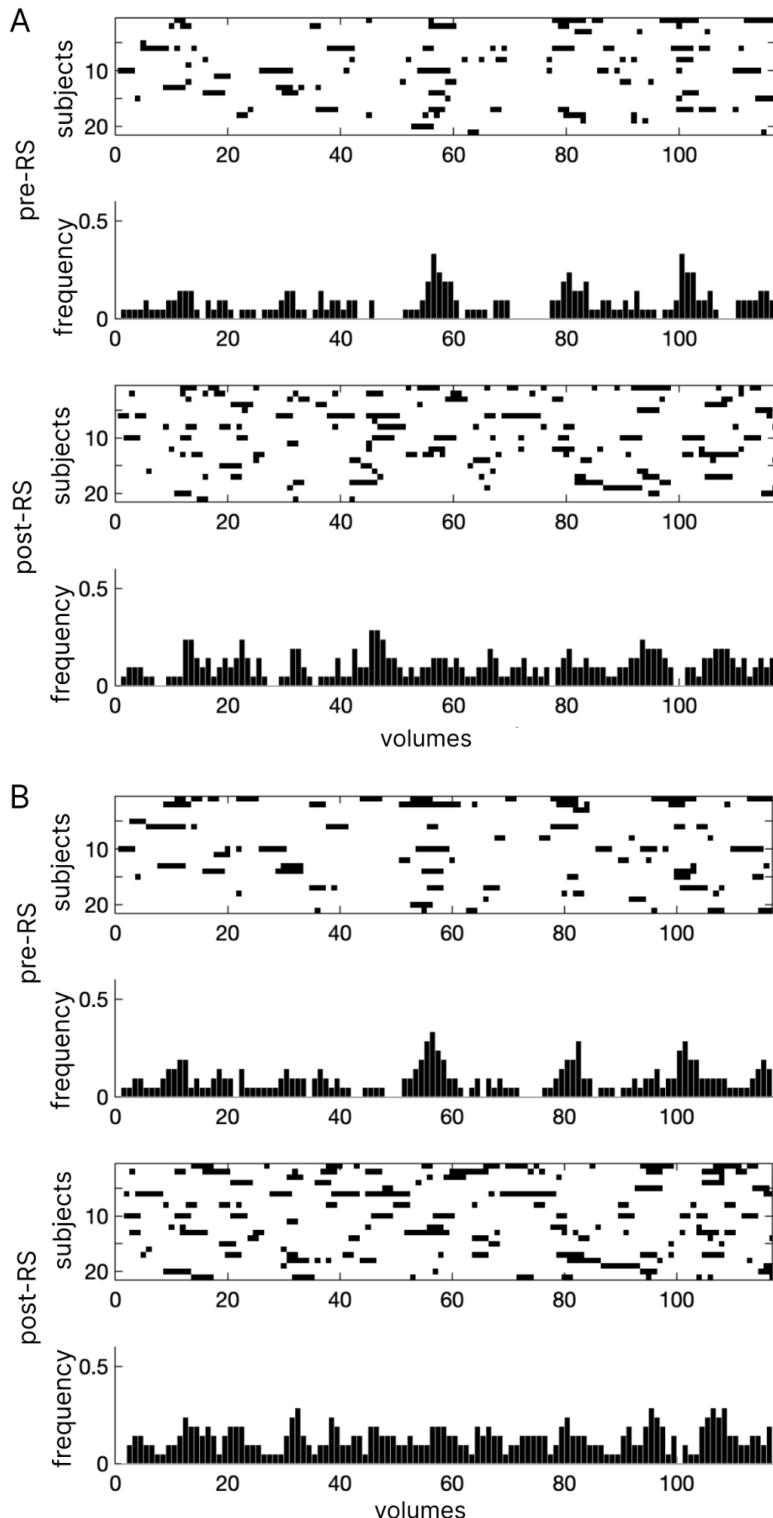
506 **Figure 7: Correlation between MVPA results and behavioral performance**

507 The correlation between the increased percentage of labeled task patterns and the  
508 decreased tracking error. The increase indicated the percentage difference between pre-  
509 RS and post-RS labeling as task patterns in the contralateral precentral and the postcentral  
510 cortex. L, left hemisphere; R, right hemisphere.

511

512

513 **Supplementary Figure**



514

515 **Supplementary Figure 1: Example of MVPA decoded labels in the left postcentral**

516 **cortex of the right-hand group**

517 The frequency of spatiotemporal patterns labeled as task patterns during rest sessions  
518 using the MVPA classification analysis (A) and the RSA (B). The black label indicates  
519 the volume classified as (A) or more similar (B) to the task pattern compared with the  
520 non-task (observation only) pattern. The upper two figures in each A and B show the  
521 distribution (upper) and frequency (lower) during the pre-RS, and the lower two figures  
522 show those during the post-RS.

523

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