Behavioral/Cognitive

Spontaneous Activity Patterns in Human Attention Networks Code for Hand Movements

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Recent evidence suggests that, in the absence of any task, spontaneous brain activity patterns and connectivity in the visual and motor cortex code for natural stimuli and actions, respectively. These "resting-state" activity patterns may underlie the maintenance and consolidation (replay) of information states coding for ecological stimuli and behaviors. In this study, we examine whether replay patterns occur in resting-state activity in association cortex grouped into high-order cognitive networks not directly processing sensory inputs or motor outputs. Fifteen participants (7 females) performed four hand movements during an fMRI study. Three movements were ecological. The fourth movement as control was less ecological. Before and after the task scans, we acquired resting-state fMRI scans. The analysis examined whether multivertex task activation patterns for the four movements computed at the cortical surface in different brain networks resembled spontaneous activity patterns measured at rest. For each movement, we computed a vector of r values indicating the strength of the similarity between the mean task activation pattern and frame-by-frame resting-state patterns. We computed a cumulative distribution function of r^2 values and used the 90th percentile cutoff value for comparison. In the dorsal attention network, resting-state patterns were more likely to match task patterns for the ecological movements than the control movement. In contrast, rest-task pattern correlation was more likely for less ecological movement in the ventral attention network. These findings show that spontaneous activity patterns in human attention networks code for hand movements.

Key words: attention networks; hand movements; representation; resting-state fMRI; spontaneous brain activity; task fMRI

Significance Statement

fMRI indirectly measures neural activity noninvasively. Resting-state (spontaneous) fMRI signals measured in the absence of any task resemble signals evoked by task performance both in topography and inter-regional (functional) connectivity. However, the function of spontaneous brain activity is unknown. We recently showed that spatial activity patterns evoked by visual and motor tasks in visual and motor cortex, respectively, occur at rest in the absence of any stimulus or response. Here we show that activity patterns related to hand movements replay at rest in frontoparietal regions of the human attention system. These findings show that spontaneous activity in the human cortex may mediate the maintenance and consolidation of information states coding for ecological stimuli and behaviors.

Received June 17, 2022; revised Jan. 18, 2023; accepted Feb. 3, 2023.

Author contributions: L.Z. analyzed data; L.Z. wrote the first draft of the paper; L.Z., L.P., G.L.S., and M.C. edited the paper; L.Z., L.P., and M.C. wrote the paper; D.K. performed research; G.L.S. and M.C. designed research.

The authors declare no competing financial interests.

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Introduction

fMRI measures changes in BOLD signals that are indirectly related to neuronal activity both at rest (spontaneous) and in task states (Biswal et al., 1995; Raichle and Mintun, 2006). Brain regions showing a temporal resting-state BOLD correlation (functional connectivity) are connected and grouped into so-called resting-state networks (RSNs) (Biswal et al., 1995; Fox and Raichle, 2007).

In the last 20 years, a large body of research has established that RSNs resemble task networks in terms of largescale topography and individual topological features (Smith et al., 2009; Tavor et al., 2016; Gordon et al., 2017). It is also possible to predict patterns of task activation based on models of inter-regional spontaneous activity fluctuations

M.C. was supported by Fondazione Cassa di Risparmio di Padova e Rovigo–Ricerca Scientifica di Eccellenza 2018 Grant Agreement 55403; Italian Ministero della Salute, Brain connectivity measured with high-density electroencephalography: a novel neurodiagnostic tool for stroke (NEUROCONN; RF-2008-12366899); Celeghin Foundation Padova CUP C94120000420007; BIAL Foundation Grant 361/18; Horizon 2020 European School of Network Neuroscience, H2020-SC5-2019-2 Grant Agreement 860563; Horizon 2020 research and innovation program; Visionary Nature Based Actions For Heath, Wellbeing & Resilience in Cities, Horizon 2020-SC5-2019-2 Grant Agreement 869505; and Italian Ministero della Salute: eye-movement dynamics during free viewing as biomarker for assessment of visuospatial functions and for Closed-loop rehabilitation in stroke (EYEMOVINSTROKE; RF-2019-12369300). L.Z. was supported by the China Scholarship Council.

(Cole et al., 2016). Accordingly, RSNs' names derive from their presumed task activation function: the default mode network (DMN) for episodic and autobiographical memory (Buckner et al., 2008); and the dorsal (DAN) or ventral attention (VAN) networks for attention and executive control (Corbetta and Shulman, 2002). Finally, RSNs features correlate with behavioral performance both in healthy subjects (Beckmann et al., 2005) and in neurologic disorders (e.g., Corbetta et al., 2018; Pini et al., 2020).

The functions of spontaneous brain activity are unknown. A recent theory has proposed that spontaneous activity plays a homeostatic function in maintaining active task circuitries (Laumann and Snyder, 2021). Accordingly, RSNs have been considered a functional scaffold of task activation patterns (Raichle, 2011; Petersen and Sporns, 2015).

However, more recent observations show that resting-state activity recapitulates the spatial distribution of activity within and across brain regions recorded during ecological stimulus or response task states. For instance, connectivity patterns that spontaneously emerge during rest in visual areas (Wilf et al., 2017; Strappini et al., 2019) are more similar to the patterns generated by naturalistic visual stimuli compared with synthetic visual stimuli. Recently, we reported that the spatial correspondence between resting and task-evoked activity patterns is categorically specific and fluctuates over time. Resting and stimulus-evoked activity was measured in visual regions showing preferences for specific stimulus categories (e.g., fusiform face area, parahippocampal place area). Spontaneously emerging patterns at rest in face-specific regions were more likely to match face-activation patterns than scene-activation patterns (vice-versa for scenes) (Kim et al., 2020). These results resonate with animal studies in the visual cortex, showing that spontaneous activity firing rates and receptive field properties are more like those induced by natural than synthetic stimuli (Fiser et al., 2004). Interestingly, this matching increases with visual cortex development as the statistics of the visual environment align with the statistics of visual cortex activity (Berkes et al., 2011).

These findings support the alternative theory that spontaneous activity patterns code for behaviorally relevant information states. Specifically, we proposed that spontaneous activity patterns represent the mechanism underlying "priors" in a predictive coding framework (Pezzulo et al., 2021). They represent an "internal model" (Poon and Merfeld, 2005) to store behaviorally relevant information during development and individual experience.

Recently, we tested whether spontaneous activity patterns in the human motor cortex code more frequently for ecological hand movements than uncommon hand movements (Livne et al., 2022). We found a more likely occurrence of spontaneous activity patterns resembling ecological hand movements in the primary motor cortex. Here we extend this study to association cortex and cognitive networks. Specifically, we examine whether spontaneously emerging activity patterns in regions of the DAN and VAN, frontoparietal (FPN), and DMN relate to task-evoked patterns for ecological and non-ecological hand movements.

Materials and Methods

Participants. In this study, we retrospectively included young healthy participants from the Washington University cohort with available resting-state and task fMRI examinations (15 participants, 7 females). Inclusion criteria for participants were normal or corrected-to-normal vision, and no history of neurologic or psychiatric diseases. The experimental protocol was approved by the Institutional Review Board of

Washington University School of Medicine. All methods used in the current study were performed in accordance with the relevant guidelines and regulations of the ethical review board. All participants provided written informed consent before the study and were compensated for their participation.

Experimental design. The imaging procedure was previously described by Livne et al. (2022). Specifically, a block-design fMRI hand movement task was performed to investigate neural activity linked with specific movements, including five consecutive runs. Participants were asked to replicate four hand movements: (1) *grip* (i.e., starting from a mid-opening position, fingers 2-5 close in a grasp movement in opposition to the thumb); (2) *extend* (i.e., starting from a mid-opening position, fingers 2-5 extend in one direction while the thumb extend in the opposite direction); (3) *pinch* (i.e., starting from a mid-opening position, the thumb and index finger complete a pinching movement); and (4) *shake* (i.e., starting from a mid-opening the fingers). This movement is not common and ecological like the others.

According to Ingram et al. (2008), who performed a statistical analysis of all hand movements performed in ecological conditions, grip and extend movements represent the most common hand gestures. The pinch was chosen based on its ecological importance in many activities. The shake movement admittedly is quite different since the wrist is in flexion rather than in a neutral position, like for the other three movements. In addition, the movement does not involve the fingers but the wrist joint.

It is important to highlight that the main goal of the experiment is to test whether task patterns are present in the resting state. The null hypothesis is that they are not. A secondary question is what is represented in these movement-related patterns. Any difference in movements is germane only to the second issue that is secondary to the study.

Participants were given a short amount of practice before scanning. In each run (5 runs total), participants performed the four different hand movements 3 times, each time for a duration of 10 s, in a random order followed by variable rest periods (20-24 s). Participants were instructed to perform one of these movements with their right hand and the movements were cued visually with a visual word cue appearing on a screen. The visual cue indicated the change in movement or rest periods. The fMRI paradigm also included three 5-minute pre-task resting-state runs and three 5-minute post-task resting-state runs. Experiment stimuli were set through Psychtoolbox running in MATLAB version 2016 (https://surfer.nmr.mgh.harvard.edu/). These movements were visually monitored by the experimenter through the scanner window, and they were quite easy to perform. Admittedly, given the absence of any accurate recordings of these movements, it is quite plausible that there was significant variability in performance both within and between subjects. However, as it will become evident in Results, the pattern of task activation was quite robust and consistent, and all relevant analyses involved resting-state scans.

MRI acquisition and imaging parameters. MRI data were acquired using a Siemens 3-T Prisma Fit MR system with a 32-channel RF head coil. Resting-state functional and task functional images were obtained using the same sequence: whole-brain EPIs with multiband factor of 3, TR = 1000 ms, TE = 25.8 ms, voxel size = 3 mm³ isotropic, 56 interleaved slices. For each participant, two high-resolution brain structural images (TR = 2400 ms; TE = 2.22 ms; voxel size = 1 mm³) were acquired using a T1-weighted multiecho MPRAGE sequence.

MRI data for 2 participants were acquired on a Siemens 3-T Tim Trio MR system with a 16-channel RF head coil. Both resting-state functional and task functional images were obtained using a multiband EPI sequence (Factor 3). The sequence parameters were the following: TR = 2000 ms, TE = 27 ms, 32 interleaved slices, voxel size = 4 mm³ isotropic. Two high-resolution brain structural images (TR = 1950 ms; TE = 2.26 ms; voxel size = 1 mm³) were acquired using a T1-weighted echo-planar MPRAGE sequence. The sequences were previously harmonized between the two scanners.

Data processing. Structural and functional preprocessing was performed using the FreeSurfer and FS-FAST processing stream (https://surfer. nmr.mgh.harvard.edu/), according to previously described procedures

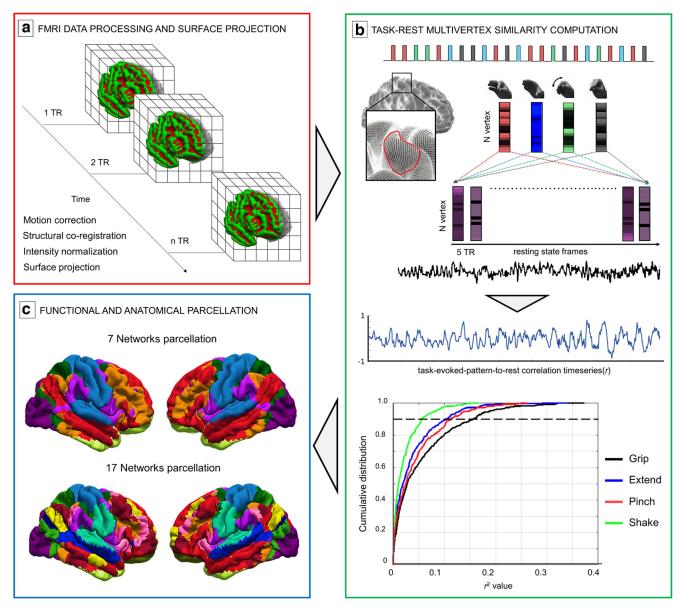


Figure 1. Flowchart of the data analysis. *a*, fMRI data were preprocessed, including motion correction, structural coregistration, intensity normalization, and surface projection. *b*, The mean activation patterns for each hand movement were computed by averaging the patterns of the frames during the most activated TRs in a specific block. This procedure yielded to four vectors, one for each hand movement. A similar vertex vector procedure was adopted for resting-state data leading to multiple vectors, one for each TR. Averaged task-evoked patterns were correlated with resting-state data. To compare the strength of the correlation, a cumulative distribution function of the squared Pearson's values was computed. *c*, Task-rest multivertex similarity analysis was assessed in two different functional network parcellations.

(Livne et al., 2022). Briefly, the following preprocessing steps were performed: (1) removal of the first four TRs to allow for magnetic field stabilization; (2) head movement correction; (3) functional data coregistration to the brain structural images; (4) intensity normalization of each frame; (5) resampling raw time series to the left and right surfaces; and (6) smoothing at 5 mm FWHM Gaussian kernel. All the fMRI data were registered to the FreeSurfer space (fsaverage template; 163,842 vertices per hemisphere).

Functional parcellation definition. RSNs were selected from Yeo's brain parcellation (Fig. 1) (Yeo et al., 2011). Specifically, two low-level sensory-motor networks (i.e., the somatomotor [SMN] and the visual network [VIS]) and three high-level control networks (i.e., the FPN, DAN, and VAN) were selected to test the hypothesis that movement patterns would be replayed in association cortex. The DMN and the limbic network (LIM), two networks involved in the memory domain (Ranganath and Ritchey, 2012; Ritchey et al., 2015), were included as control networks, as we do not expect any "replay" linked to the top-down control of motor action planning and execution.

Task-rest multivertex similarity analysis. To investigate the similarity between resting state and task patterns evoked by different hand movements, we performed a multivertex linear analysis. The analysis was conducted by projecting voxels to the cortical surface, thus moving from voxel to vertex space: voxels become vertices of a surface grid based on the envelope of the cortex (vertices represent the points at which two or more lines connect), representing the smallest resolution element on the brain surface. Accordingly, for each participant, the preprocessed fMRI is resampled to native brain surface space. Within each network, we computed the multivertex spatial pattern of activation for the four movements considered. An averaged task-evoked activity pattern for each hand movement (built from all the task runs) was extracted for each network, separately. Specifically, these averaged activation patterns were computed by averaging the signal of the frames within the range of 10-18 s after the beginning of the movement trial. This range was selected according to our previous study as it was the most sensitive range to discriminate between the different hand movements and showed a larger BOLD signal change (Livne et al., 2022). A total of four averaged vectors

Table 1. Vertex numbers for the functional network parcellations^a

	Left hemisphere	Right hemisphere
7-network template		
VIS	21,632	22,519
SMN	29,778	30,207
DAN	17,511	17,604
VAN	17,392	19,402
LIM	11,380	11,614
FPN	16,635	22,330
DMN	35,314	26,056
17-network template		
SMN A	14,687	14,516
SMN B	12,670	12,148
DAN A	8474	9267
DAN B	8612	9150
SN/VAN A	12,059	13,053
SN/VAN B	7098	9688

^aThe number of vertices for each network is shown.

were computed, one for each hand movement. The length of these vectors represented the number of vertices for each network. A vector of the same length was computed for each resting-state frame. We then correlated the task-evoked vector with the resting-state data. This procedure yielded n = 888 or n = 438 (for the 2 participants performing the examination with the Siemens machine) Pearson's values for each movement. To compare the strength of the correlation between task-evoked and resting-state signals, we computed the cumulative distribution function of these r^2 values. According to our previous analysis, we identified the 90th percentile cutoff value (higher cutoffs indicate higher similarity between activation and spontaneous fluctuations). These cutoff values were inserted as the dependent variable in an analysis of variance (ANOVA).

Statistical analysis. Two different models were tested. The first model (four-way interaction) investigated the similarity pattern accounting for movement, brain hemisphere (left and right), network, and time (pre-task and post-task). A *p* value < 0.05 was considered significant. In the second model (three-way), we tested the network-movement-hemisphere interaction independently for each time point (pre-task and post-task). A *p* value < 0.025 Bonferroni-corrected was set as significant considering the two independent analyses.

17-network analysis. The analyses were repeated, including a more fine-grained parcellation (Yeo's 17 network atlas) to ensure that results would be robust across different subnetworks. This parcellation splits the seven main neural networks into two/three multiple subsystems along a caudal/rostral or superior/inferior or anterior/posterior gradient.

Network movement activation control analyses. For each network included in the main analysis (7 network space), we computed an averaged brain movement activation value. This analysis was performed to investigate whether networks exhibiting differences in the task-rest similarity pattern showed also higher activation during task. To this aim, a whole-brain statistical t map was computed (hand movements vs baseline contrast) and projected at surface level. T values for vertices were averaged within each network parcellation to compute a hand movement network activation score. Differences in activation scores between networks were compared through an ANOVA. P values were corrected for multiple comparisons. This analysis was repeated across all movements. Additionally, the same analysis was performed for each hand movement to assess whether higher task activation for specific gestures could drive differences between movements in task-rest similarity. Differences in the activation pattern across movements were assessed by means of an ANOVA. Finally, as a control analysis to ensure that the variability in movement magnitude of activation did not significantly affect the estimation of the spatial patterns of movement-related activation, we measured the correlation across task activation patterns for each network. This similarity matrix of movement-evoked patterns (i.e., averaged activation patterns used in the main analysis) was computed for each network and each participant by Pearson's correlation.

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Interactions	F statistic	р	F statistic	р	
Four-way	7-network analysis		17-network ana	17-network analysis*	
	0.70	0.809	0.85	0.618	
Three-way	7-network pre-task analysis		7-network post- analysis	7-network post-task analysis	
	2.02	0.010	1.53	0.081	
	17-network pre-task analysis*		17-network pos analysis*	17-network post-task analysis*	
	2.55	0.002	1.99	0.017	

^aThe first model included four independent variables: movement, brain hemisphere (left and right), network, and time (pre-task and post-task). The second model tested for network, movement, and hemisphere interactions separately for the two time points (pre, post). Since the main analysis was conducted using the 7network parcellation, we also performed a "high-resolution" network parcellation analysis on the 17-network cortical parcellation. In the main four-way analysis, there was no significant effect of movement \times time \times hemisphere \times network. The three-way interaction computed separately for pre-task and post-task showed a significant effect in the pre-task resting state. The 17-network malysis showed no significant interaction effect of movement \times time \times hemisphere \times network, but a significant interaction effect of movement \times hemisphere \times network for both pre-task and post-task resting state data.

*The 17-network ANOVA was performed within the SMN, DAN, and VAN to pair the number of networks (n = 6) with the main analysis (n = 7).

Table 3. Statistical results for the main effect of movement within each functional network (pre-task resting state)^a

	Left hemisphere		Right hemisphere	
	F	р	F	р
7-network template				
VIS	1.39	0.258	0.23	0.873
SMN	7.75	< 0.001	1.27	0.297
SMN-active ROI	0.22	0.883		
DAN	5.25	0.004	1.41	0.345
VAN	1.77	0.168	3.53	0.023
LIM	1.54	0.218	0.57	0.636
FPN	0.76	0.523	0.7	0.558
DMN	0.75	0.527	1.89	0.146
17-network template				
SMN A	21.35	< 0.001	1.44	0.245
SMN B	1.07	0.371	0.15	0.930
DAN A	1.04	0.385	1.82	0.159
DAN B	3.92	0.015	0.26	0.851
VAN A	0.28	0.841	1.74	0.173
VAN B	1.83	0.157	0.89	0.455

^aPost hoc analysis showed a movement effect for the left SMN. To assess whether this effect was driven by the portion of motor cortex activated by the movements (Livne et al., 2022), we repeated the analysis, masking the motor activation ROI in the left SMN. The movement effect within the left SMN was no longer significant. This result suggests that SMN similarity pattern specifically occurred in the subregion of motor cortex driven by the movements. Furthermore, we found a significant movement effect in the left DAN and the right VAN. The FPN, DMN, LIM, and VIS did not show significant task-rest similarity (p > 0.05). Results from the 7-network parcellation were confirmed in the 17 networks. *Post hoc* analysis showed a significant effect within the left superior SMN subnetwork (SMN A). A significant effect of movement was reported within the left anterior DAN subnetwork (encompassing the frontal eye fields and superior parietal lobule, DAN B) for pre-task spontaneous fluctuations).

Results

A total of 15 participants (7 females, mean age 26.5) were included in the study. For task fMRI data, only 1 participant showed a "protocol deviation," performing four runs instead of five. Similarly, for post-task resting MRI data, 1 participant performed two resting-state runs instead of three.

Similarity analysis of spontaneous and task-evoked activity patterns

The number of vertices for each network is shown in Table 1. Regarding the four-way analysis, there was no significant effect of movement × time × hemisphere × network ($F_{(18,252)} =$ 0.70; p = 0.809) (Table 2). The three-way interaction computed

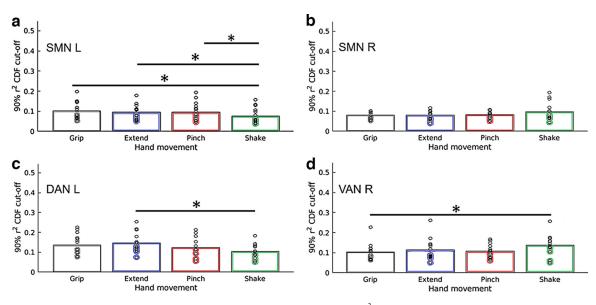


Figure 2. A distribution representation for hand movements in the human brain for pre-task resting state. *a*, r^2 cutoff values for the different hand movements' patterns in the left SMN. Grip showed the highest value. The lowest value was reported for Shake movement. A significant effect for Extend and Pinch compared with Shake was also reported. These effects survived Bonferroni multiple comparison correction. *b*, r^2 cutoff values for right SMN. No significant differences were found between different movements. *c*, r^2 cutoff values of the four different hand movements' patterns in the left DAN. The difference between the Extend and the Shake conditions was statistically significant, surviving multiple comparison correction. *d*, r^2 cutoff values in the right VAN. Shake patterns showed the highest cutoff value compared with Grip, surviving after Bonferroni multiple comparison correction. *Significant difference.

separately for pre-task and post-task showed a significant effect in the pre-task resting state ($F_{(18,252)} = 2.02$; p = 0.010, $\eta_p^2 = 0.126$) (Table 2). *Post hoc* analysis showed a movement effect for the left SMN ($F_{(3,42)} = 7.75$, p < 0.001, $\eta_p^2 = 0.356$; Table 3), contralateral to the hand used to perform the movements. Specifically, grip, extend, and pinch evoked multivertex activity patterns showed higher similarity with spontaneous multivertex activity patterns than the control movement (shake) after Bonferroni multiple comparison correction (grip vs shake: p < 0.001, extend vs shake: p = 0.008, pinch vs shake: p = 0.007) (Fig. 2). To assess whether this effect was driven by the portion of motor cortex activated by the movements (Livne et al., 2022), we repeated the analysis masking the motor activation ROI in the left SMN (Fig. 3). The movement effect within the left SMN was no longer significant $(F_{(3,42)} = 0.22; p = 0.88)$ (Table 3). This result suggests that SMN similarity pattern specifically occurred in the subregion of motor cortex driven by the movements.

Furthermore, consistent with our prediction that high-level control networks contribute to the representation of movement in the resting state, we found a significant movement effect in the left DAN ($F_{(3,42)} = 5.25$, p = 0.004, $\eta_p^2 = 0.273$) (Table 3; Fig. 2). Evoked activity triggered by the extend movement was more like rest patterns than the control shake movement (extend vs shake, p = 0.003, significant after Bonferroni multiple comparison correction). There was also a trend toward a statistically significant similarity task-rest for the grip movement (grip vs shake, p = 0.054). Hence, more ecological and familiar movements occur more frequently at rest in the DAN than a novel nonfamiliar movement.

In contrast, we recorded significantly higher similarity for the control (shake) movement compared with the ecological movement (grip) in the right VAN (movement effect: $F_{(3,42)} = 3.53$, p = 0.023, $\eta_p^2 = 0.201$), after Bonferroni correction (shake vs grip, p = 0.033), with Pinch showing a trend toward statistical significance (shake vs pinch, p = 0.062). The FPN, DMN, LIM, and VIS did not show significant differences in task-rest similarity (p > 0.05).

a Non-activation somatomotor

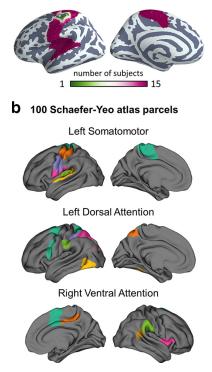


Figure 3. Parcels presentation. *a*, Nonactivation SMN. For each participant, we identified the nonactivation SMN ROI by excluding from the SMN the activation ROI reported in our previous publication (Livne et al., 2022). For presentation purposes, all ROIs were projected on an average surface and summed together. Color scale represents the number of participants for which the specific vertex on the surface was included in the ROI. *b*, Analysis of individual parcels from the SMN, DAN, and VAN based on the Schaefer 100 parcel atlas (Schaefer et al., 2018). A significant result was reported for a parcel in the SMN (orange parcel) overlapping with the motor activation region from Livne et al. (2022). No significant results were reported for parcels in either the VAN or DAN.

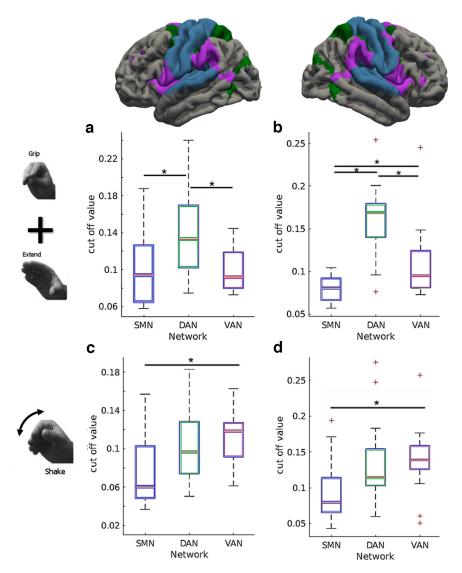


Figure 4. A distribution representation for hand movements in terms of networks for pre-task resting state. *a*, DAN showed the highest cutoff value of ecological movements (averaged Grip and Extend) in the left hemisphere compared with both SMN and VAN. *b*, This result in *a* was echoed in the right hemisphere, along with a significant right VAN higher value compared with the SMN. *c*, VAN showed higher cutoff value compared with SMN for the control movement (Shake) in the left hemisphere. *d*, This result in *c* was echoed in the right hemisphere. *Significant difference.

We examined the presence of task-rest similarity as a function of hand movements in the post-task resting-state scan. The results only showed a trend difference ($F_{(18,252)} = 1.53$; p = 0.081) (Table 2). This result was explained by an overall increase of task-rest similarity for all movements. Indeed, the 90th percentile cutoff values were higher overall in the posttask resting-state scan (cutoff: $r^2 = 0.123$) compared with the pre-task resting-state scan (cutoff: $r^2 = 0.115$). This difference was statistically significant (main effect of time in the four-way ANOVA: $F_{(1,252)} = 6.22$; p = 0.026, $\eta_p^2 = 0.308$).

To investigate whether specific network regions drive the significant effects reported, we ran a *post hoc* multivertex linear analysis separately for each parcel belonging to the SMN, DAN, and VAN (see Fig. 3*b*) of the Yeo's 7-network atlas Schaefer 100 parcel version (Schaefer et al., 2018). We found a significant main effect in the SMN ($F_{(3,42)} = 16.84$, p < 0.001, $\eta_p^2 = 0.546$) for a single parcel overlapping with the motor activation region previously reported (Livne et al., 2022). By contrast, no significant results were observed for individual parcels of the DAN and the VAN (p > 0.05).

Post hoc network multivertex analysis

We performed an additional post hoc analysis to compare the 90th percentile cutoff values between networks showing a significant effect in the three-way interaction analysis (i.e., SMN, DAN, and VAN). Specifically, for each hemisphere, we computed pairwise differences (SMN vs DAN; SMN vs VAN; DAN vs VAN), comparing both ecological movements (averaged cutoff score between grip and extend) and the control movement (shake). In the DAN, we found higher task-rest similarity values for ecological movements in both hemispheres (left: DAN vs SMN: p = 0.029, DAN vs VAN: p = 0.009; right: DAN vs SMN: *p* < 0. 001, DAN vs VAN: *p* = 0.005), along with a significantly higher similarity for the right VAN compared with the SMN (p = 0.038) (Fig. 4). For the control movement, the VAN showed the highest values, significantly different compared with the SMN (left: p = 0.022; right: p = 0.018) (Fig. 4).

Seventeen networks parcellation

Results from the 7-network parcellation were confirmed in the 17 networks (Table 2). For the 17-network parcels, we included SMN, DAN, and VAN subnetworks (e.g., superior/inferior SMN; anterior/posterior DAN; anterior/posterior VAN) in the models to pair the number of networks included in the main analysis. The four-way interaction showed no significant effect when time was included in model (movement \times time \times hemisphere \times network: $F_{(15,210)} = 0.85$; p = 0.618). By contrast, the three-way interaction reported a significant effect (movement imes hemisphere imesnetwork) at both time points (pre-task: $F_{(15,210)} = 2.55, p = 0.002, \eta_p^2 = 0.154;$ post-task: $F_{(15,210)} = 1.99$, p = 0.017, $\eta_p^2 =$ 0.125) (Table 2). Post hoc analysis showed a

significant effect within the left superior SMN subnetwork (pretask: $F_{(3,42)} = 21.35$, p < 0.001, $\eta_p^2 = 0.604$; post-task: $F_{(3,42)} = 10.75$, p < 0.001, $\eta_p^2 = 0.434$) (Table 3). Specifically, grip, extend, and pinch-evoked activity showed higher similarity with spontaneous patterns compared with shake (pre-task: grip vs shake: p < 0.001, extend vs shake: p < 0.001, pinch vs shake: p < 0.001; post-task: grip vs shake: p < 0.001, extend vs shake: p = 0.004, pinch vs shake: p < 0.001). A significant effect of movement was reported within the left anterior DAN subnetwork (encompassing the frontal eye fields and superior parietal lobule) for pre-task spontaneous fluctuations: $F_{(3,42)} = 3.92$, p = 0.015, $\eta_p^2 = 0.219$). Specifically, ecological movement-evoked patterns showed significantly higher similarity with the pre-task spontaneous patterns compared with the control movement (grip vs shake, p = 0.038; extend vs shake, p = 0.033).

Network activation comparison control analyses

There was a significant network difference in the level of activation during the motor task involving all four movements (left: $F_{(6,84)} = 37.23$, p < 0.001, $\eta_p^2 = 0.727$; right: $F_{(6,84)} = 18.56$, p < а

b

sphere. *Significant difference.

0.001, $\eta_p^2 = 0.570$) (Fig. 5). In the left hemisphere, the SMN showed the strongest level of activation (p < 0.001 for all comparisons), followed by a significant activation of the VAN (p < 0.001 compared with VIS, LIM, FPN, and DMN). In the right hemisphere, the VAN showed the highest activation (p < 0.001 for all comparisons) (Fig. 5). When we considered the movements separately, we found a similar trend in the distribution of the activation values across networks (Fig. 6). The statistical analysis showed no differential movement effect (movement main effect, $F_{(3,252)} = 0.98$, p = 0.412; movement \times network, $F_{(18,252)} = 2.66$, p < 0.001, $\eta_p^2 =$ 0.160).

Finally, we showed that the three ecological and more familiar movements yielded a pattern of task activation that was more consistent and similar than the control movement in the left SMN (Fig. 7), echoing our previous results (Livne et al., 2022) showing higher similarity pattern between ecological movements in the activated ROI (Fig. 7). Notably, brain networks showing significant results (SMN, DAN, and VAN) were the circuits also showing higher similarity between movements, compared with networks reporting null effects (DMN, LIM, and FPN).

Moreover, based on previous results by Kim et al. (2020) who had shown a significant across-subject correlation between the magnitude of task activation and rest-task pattern similarity, we have also investigated the correlations between each movement versus base-

line activation (*t* value) and the 90th percentile cutoff value for each movement (r^2) in each network. We found a marginal significance (not surviving multiple comparisons) within (1) left SMN for the Extend: r = 0.56, p = 0.032 and the Pinch: r = 0.61, p = 0.017; (2) right VAN for the Pinch: r = 0.61, p = 0.014; (3) right LIM for the Extend: r = -0.56, p = 0.032; and (4) right DMN for the Shake: r = -0.53, p = 0.040.

Discussion

Here, we investigated spontaneous representation of hand movements in association cortex and cognitive brain networks. Several results are worth discussing.

First, we replicated the observation that multivertex activity patterns related to behaviorally relevant states (movements) replay in spontaneous activity. This replay occurs not only in the sensory regions (Kim et al., 2020; Livne et al., 2022) but also in cognitive networks. Importantly, these patterns were present both before and after the performance of the movements. Hence, they do not represent the effects of short-term learning.

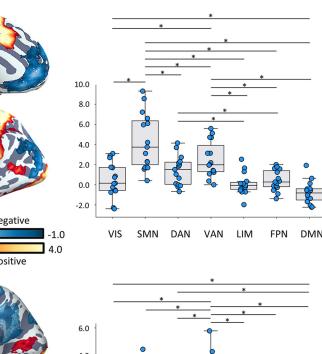
It is essential to clarify what we mean when we speak about the similarity of rest and task patterns. We mean that multivertex spatial patterns of activity in their temporal fluctuation at rest more strongly correlate (both positively and negatively) with the multivertex patterns evoked by the task. While the mean distribution of similarity values between the resting and task-evoked multivertex patterns is zero for all tasks, the tails of the distribution of similarity values for the represented task are more positive/negative than for the control condition. Here the comparison was made between ecological hand movements and an unusual, less ecological movement.

These results extend to attentional networks (Livne et al., 2022) in primary motor cortex. Similar task-rest pattern similarity also occurs in visual cortex in both humans (Kim et al., 2020) and animals, including monkeys (Omer et al., 2019), ferrets (Berkes et al., 2011), and cats (Kenet et al., 2003). The replay of behaviorally relevant visual or motor patterns in spontaneous activity may explain why on average spontaneous activity is more similar to activity evoked by natural than synthetic stimuli.

Our second result is that movement-related resting patterns were specific for different movements in different networks. In the SMN, resting patterns were more frequent for ecological movements than the control noncommon one (Fig. 2). This difference occurred specifically in the motor cortex contralateral to the performing hand, which was also more strongly active, and in the dorsal regions of the SMN representing the hand. In other words, the spontaneous activity patterns strongly colocalized with the movement-evoked patterns.

In contrast, the effects in the attention (DAN, VAN) networks were more distributed. We did not find a specific region driving

8.0 6.0 4.0 2.0 0.0 -2 0 t-values - negative VIS SMN DAN VAN LIM FPN DMN -4.0 -1.0 1.0 4.0 t-values - positive 6.0 4.0 2.0 0.0 -2.0 VIS SMN DAN VAN LIM FPN DMN Figure 5. Averaged statistical map of task-evoked patterns. *a*, Averaged *t* map for hand movements versus baseline contrast. **b**, VAN showed the highest t value in the right hemisphere, while SMN showed the highest t value in the left hemi-



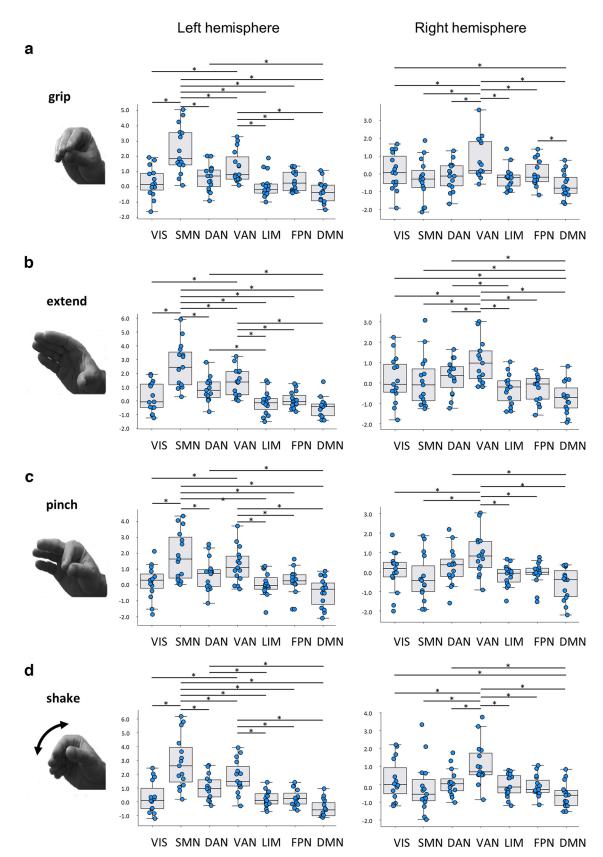


Figure 6. Averaged statistical map of movement-evoked patterns. Comparison between *t* value in each network for the contrast of each hand movement versus baseline. *a*, Grip versus baseline. *b*, Extend versus baseline. *c*, Pinch versus baseline. *d*, Shake versus baseline. *Significant difference.

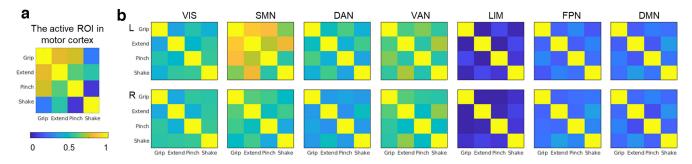


Figure 7. Similarity matrix of movement-evoked patterns. Color scale represents the mean Pearson *r* values across all the participants. *a*, Similarity between the Grip, Extend, and Pinch patterns was higher than their similarity to the Shake pattern in the active ROI in the motor cortex obtained from Livne et al. (2022). *b*, Similarity between the Grip, Extend, and Pinch patterns was higher than their similarity to the Shake pattern in the left SMN. Other networks did not have this similarity.

the effect in these networks, suggesting that the coding of a specific hand movement during rest was diffuse in the multivertex activity pattern across multiple network regions.

In the DAN the resting-state patterns coded more frequently for ecological movements, while in the VAN resting-state patterns coded more frequently for the uncommon movement. One possible interpretation based on the idea of predictive coding and attention is that resting-state patterns in the DAN underlie top-down attention signals for motor planning, which would be more common for ecological movements. In contrast, restingstate patterns in the VAN may be coding for prediction errors or mismatch in motor expectations. This interpretation is consistent with functional anatomic models of human attention (Corbetta and Shulman, 2002; Corbetta et al., 2008).

Another possibility is that this rest replay is "motor" in nature. The VAN and DAN contain regions in frontoparietal cortex involved in motor control and action planning (Andersen and Cui, 2009). Accordingly, neither DMN nor VIS not involved in sensory-motor planning showed any significant difference among different kinds of movements in task-rest similarity. Moreover, in the 17-network analysis, there was a significant movement effect in the left DAN-B (encompassing frontal eye fields and superior parietal lobule, regions surrounding the motor-activated region) rather than in more sensory DAN-A (including fusiform, lateral occipital, inferior temporal, and parietal). This interpretation is in line with previous literature suggesting that action-related information stores in parallel across multiple regions that work in concert within a functional system (Gallivan and Culham, 2015; Galletti and Fattori, 2018; Hardwick et al., 2018). It is also consistent with the concept of "representational connectivity," that is, occurrence of multivertex patterns of activity related to a specific stimulus or movement (as in this case) across multiple areas. In human extrastriate visual cortex, we showed the co-occurrence of "face-related" activity patterns across multiple facespecific regions: the same for a "scene-state" in scene-coding regions (Kim et al., 2020). These results are consistent with our theory, which proposes that spontaneous activity codes for behaviorally relevant states both in terms of connectivity and spatial patterns of activity within/across regions (Pezzulo et al., 2021).

We suggest that spontaneous activity patterns in the human association cortex may resemble replay sequence activity in the hippocampus (Liu et al., 2019). Cells activated during memory tasks fire spontaneously along an organized sequence during rest activity. Notably, this firing seems to integrate past and recent experiences (Carr et al., 2011; Wu et al., 2017). They also occur in anticipation of novel sequences or preplay (Dragoi and Tonegawa, 2011). Recently, Schuck and Niv (2019) registered hippocampal BOLD signals at rest and reported that spontaneous fluctuations recapitulate sequential activation induced by a decision-making task. These findings suggest that brain regions represent signals linked with previous experience, thus providing computational benefits for subsequently achieving fast and flexible responses (Schuck and Niv, 2019; Pezzulo et al., 2021). In line with these observations, our findings provide evidence of sequential "offline" reactivation of hand gestures in large-scale networks underlying attention and action planning. While in the DAN these patterns more strongly relate to predictable movements in the sense of being familiar and ecological, in the VAN the relationship is more robust with uncommon movements. Hence, spontaneous fluctuations in attentional networks may act as a fundamental process to maintain and prepare within the continuum of hand gestures, leading to a stable set of neural signals (Buzsaki and Draguhn, 2004; Gratton et al., 2018).

The lateralization of the hemispheric effects is also significant. Task-rest similarity was higher in the left DAN for ecological movements and in the right VAN for the unusual control movement. The left lateralization in the DAN (as in the SMN) is consistent with using the right-hand during task execution, or a left hemisphere dominance for movement representations in right-handed subjects (Rushworth et al., 2001; Kuhtz-Buschbeck et al., 2003; Karolis et al., 2019). The right lateralization in the VAN agrees with the attention literature (Corbetta et al., 2008; Vossel et al., 2014).

A final comment concerns the results in the post-task resting state. While we did not replicate a significant modulation of ecological versus noncommon movements in the main analysis, there was evidence for significant modulation in the 17-network analysis. Moreover, we found a significantly higher task-rest similarity for all movements in the post-task than in the pre-task restingstate scan. These findings may suggest that during the experiment, participants practiced all hand movement tasks for nearly 30 min, inducing a change in the post-task patterns of spontaneous activity, making the movement patterns more common. Short-term learning modulation of resting-state connectivity, not spatial activity patterns as in this case, has been shown in the motor, visual, and hippocampus systems (Albert et al., 2009; Lewis et al., 2009; Baldassarre et al., 2012; Guerra-Carrillo et al., 2014).

Limitations

The main limitation is the lack of kinematic measurements as participants performed hand movements in the scanner. An experimenter constantly monitored participants' performance, but we did not set up any specific recordings. However, as shown in Figure 7, the activation patterns were highly consistent and distinguished between ecological and noncommon movements, both at group and single-subject levels. Hence, whatever performance variability (within a scan or across subjects) occurred within/ between movements should have influenced the robustness of finding similar task-to-rest patterns. However, the robustness of our results negates the null hypothesis of no task-rest similarity differences between movements.

Moreover, we cannot interpret the difference between the four kinds of movements. While grip and extend were taken from Ingram et al. (2008)'s synergies, pinch and shake were selected ad hoc. The "shake" movement involved different muscles and actions from the other finger movements. Also, it is a movement not as frequently performed or as functionally relevant. However, the frequency or novelty of movements was not varied parametrically. Notwithstanding these limitations, the study's primary goal was to show the rest-task similarity of distributed activity patterns in different networks and for different movements. Our goal was not to characterize resting motor representations in terms of specific behavioral dimensions (e.g., frequency, effectors such as finger vs wrist). While the latter is an important goal, the demonstration of systematic variation of the task-rest similarity of activity patterns comes first. It was the main aim of the present work, which we believe we accomplished.

Additionally, we selected two specific parcellations (7 and 17 networks) (Yeo et al., 2011). The parcellation with higher dimensionality improved accuracy. There was a more substantial similarity in the superior SMN network in line with hand somatotopy. Accordingly, a new atlas based on a data-driven approach might increase the frequency of the behaviorally relevant resting-state patterns (Ren et al., 2019). Finally, our sample size was small, and a prominent individual variability was reported for the similarity patterns between different movements, although the robustness of the effects is evident.

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