

Uncertainty-Aware Spatiotemporal Graph Learning for Individualized Cortical Parcellation and Somato-Cognitive Integration in the Developing Brain

Yuxin Xue¹[0009–0003–0289–0713], Wen Li³, Jianyu Li⁴, Xin Jin⁵, Jingguo Dai⁶, Haozheng Shen⁶, Luqi Cheng⁷, Weiyang Shi³, Yuanchao Zhang¹, Yongfu Hao⁶, Wenjie Zhou⁸, Huixiong Zhang^{1*}, and Yu Zhang²[0000–0001–7159–4561]**

¹ University of Electronic Science and Technology of China, Chengdu, China
hzhang@uestc.edu.cn

² School of Psychology, Shanghai Jiao Tong University, Shanghai 200030, China
yuzhang2bic@gmail.com

³ Brainnetome Center, Institute of Automation, Chinese Academy of Sciences, Beijing, China

⁴ West China Hospital of Sichuan University, Chengdu, Sichuan, China

⁵ School of Life Science and Technology, University of Electronic Science and Technology of China, Chengdu, Sichuan 610054, China

⁶ Zhejiang Lab, Hangzhou, Zhejiang, China

⁷ School of Life and Environmental Sciences, Guilin University of Electronic Technology, Guilin 541004, China

⁸ Songjiang Research Institute, Shanghai Key Laboratory of Emotions and Affective Disorders, Songjiang Hospital Affiliated to Shanghai Jiao Tong University School of Medicine, Shanghai, China

Abstract. Individualized cortical parcellation remains challenging due to substantial inter-subject variability and the limited generalizability of group-derived templates, particularly in transitional zones where functional topography is heterogeneous. To address this, we propose STGraph-Parcel, an uncertainty-aware spatiotemporal graph learning framework that derives individualized cortical areal maps directly from vertex-wise fMRI time series. Incorporating a population-level adolescent atlas as a soft group prior, our approach preserves anatomical consistency while accommodating individual variations. Methodologically, we integrate explicit temporal modeling with spatial graph convolutions: a dual-channel Gated Recurrent Unit (GRU) integrates raw vertex signals with attention-weighted topological neighborhood representations to extract temporal embeddings. These embeddings are subsequently aggregated via Graph Convolutional Networks (GCNs) across neighbors on the cortical mesh. Evaluated on naturalistic movie-watching fMRI from the Healthy Brain Network (HBN) cohort, our method improves intra-subject functional homogeneity and test-retest reliability. Furthermore, STGraph-Parcel

* Corresponding authors.

** Corresponding authors.

generates probabilistic maps and evaluates uncertainty of parcel assignment for each vertex. Using entropy-based uncertainty quantification, the model identifies high-entropy vertices as functional integration zones. Notably, these regions predominantly localize within the Somato-Cognitive Action Network (SCAN) and adjacent auditory-linguistic systems. By revealing elevated cross-network participation and developmental modulation in these SCAN zones, our study underscores their role during youth brain maturation. Ultimately, this framework advances precision functional mapping and provides a computational lens for tracking individualized neurodevelopmental trajectories in adolescent populations.

Keywords: Spatiotemporal Graph Learning · Individualized Cortical Parcellation · Uncertainty Estimation · Somato-Cognitive Action Network (SCAN) · Adolescent Neurodevelopment · fMRI.

1 Introduction

The primary motor cortex has traditionally been described as a somatotopic homunculus [11, 13], yet recent work identifies inter-effector territories that depart from strict somatotopy [3, 5]. Substantial inter-individual variability, particularly during development [4, 6, 10], underscores the need for individualized parcellation beyond group-averaged atlases [7, 15].

We introduce an uncertainty-aware spatiotemporal graph learning framework that models vertex-wise BOLD time series during naturalistic movie watching [14]. Neighborhood self-attention and dual-channel GRU encoding capture local temporal dynamics prior to topology-constrained graph convolution for areal classification, with a population-level atlas prior incorporated as soft regularization. Entropy derived from probabilistic predictions identifies reproducible high-uncertainty regions aligned with previously described inter-effector territories [1, 3]. This framework provides a temporally informed and uncertainty-calibrated approach to individualized cortical mapping.

2 Method

HBN Dataset Neuroimaging data were obtained from the Healthy Brain Network (HBN), including naturalistic movie-watching fMRI. After preprocessing and quality control, 200 participants were used for training, 50 for validation (age range 5-22 years; mean age 10.7), and an independent test cohort of 196 participants (age range 5-21 years; mean age 12.5). No participant overlapped across cohorts. The movie run lasted 10 minutes ($TR = 0.8$ s) and was divided into two non-overlapping 5-minute segments during training to enhance data efficiency and stabilize temporal representation learning.

Individualized Brain Atlas Pipeline We developed a spatiotemporal graph framework to generate individualized cortical parcellations directly from vertex-wise BOLD time series during naturalistic movie watching (Fig. 1). Temporal

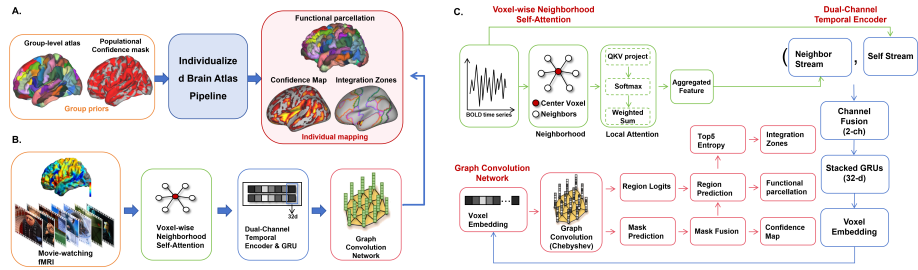


Fig. 1. Uncertainty-aware individualized parcellation framework.

dynamics and surface topology are jointly modeled using attention-GRU encoding and graph convolution, avoiding reliance on static functional connectivity matrices. The model outputs probabilistic vertex-wise labels, enabling entropy-based uncertainty analysis to identify transitional integration zones at the group level.

Spatiotemporal Graph Encoding We designed a unified spatiotemporal graph framework to derive individualized cortical representations directly from vertex-wise BOLD time series (Fig. 1). For each vertex, a fixed surface-based neighborhood was defined, and multi-head local self-attention dynamically weighted neighboring signals at each time point. The attention-aggregated signal was combined with the original time series to form a dual-channel temporal input. Temporal dynamics were encoded using stacked GRU layers, jointly modeling intrinsic vertex activity and neighborhood-modulated interactions while preserving time-resolved information under naturalistic stimulation. The resulting embeddings were propagated across the cortical mesh using multi-order graph convolutions with Chebyshev filters, capturing multi-hop spatial dependencies while respecting surface topology. The network output parcel logits and probabilistic confidence estimates (Fig. 1C-E).

Uncertainty Modeling and Optimization An uncertainty-aware branch predicted vertex-level confidence values, stabilized via exponential moving average smoothing and fused with a group-level probabilistic atlas prior derived from a preadolescent Brainnetome atlas [9] to balance individual specificity and population constraints. Specifically, the group probabilistic atlas was concatenated with first-layer GCN features to estimate a vertex-wise confidence map, and only vertices with confidence greater than 0.5 were supervised by atlas-derived pseudo-labels using cross-entropy loss. Thus, the atlas prior served as weak supervision rather than a hard constraint. Training combined cross-entropy loss, cross-session consistency objectives, and mask regularization to promote stable and biologically plausible parcellations. The cross-session consistency objective penalized inconsistent probabilistic assignments of the same cortical vertex across repeated movie segments from the same subject. After training, entropy

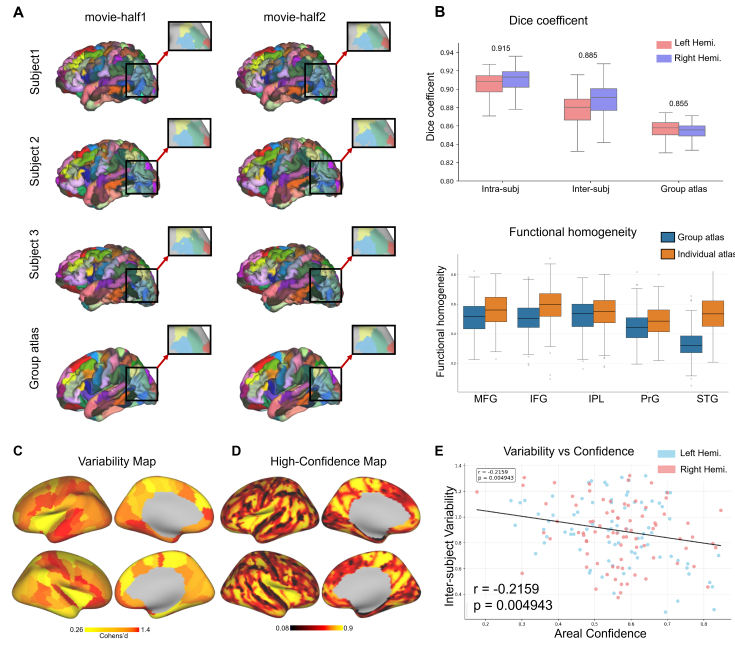


Fig. 2. Individualized parcellation captures robust topological heterogeneity.

was computed from the top five predicted class probabilities. A three-component Gaussian Mixture Model separated uncertainty regimes, and vertices assigned to the high-entropy component (posterior > 0.95) were retained. Surface-based denoising and merging across two movie runs ensured reproducibility. Reproducible high-entropy vertices were aggregated across subjects to define group-level integration zones within SCAN and adjacent auditory-linguistic systems.

3 Results

Reliable and Individual-Specific Parcellation To assess reliability and functional specificity (Fig. 2), we examined test-retest consistency, functional homogeneity, inter-subject variability, and model-derived confidence. Individualized maps showed high within-subject consistency across movie halves while preserving inter-individual differences relative to the group atlas (Fig. 2A). Dice coefficients were highest intra-subject (0.915), lower inter-subject (0.885), and lowest relative to the group atlas (0.855), indicating stable yet individualized organization (Fig. 2B). Functional homogeneity during movie watching was higher in individualized atlases. Variability was greater in association cortex and lower in sensory regions, mirroring the confidence map. Variability and confidence were negatively correlated ($r = -0.2159$, $p = 0.0049$; Fig. 2C-E), supporting the biological relevance of uncertainty estimates.

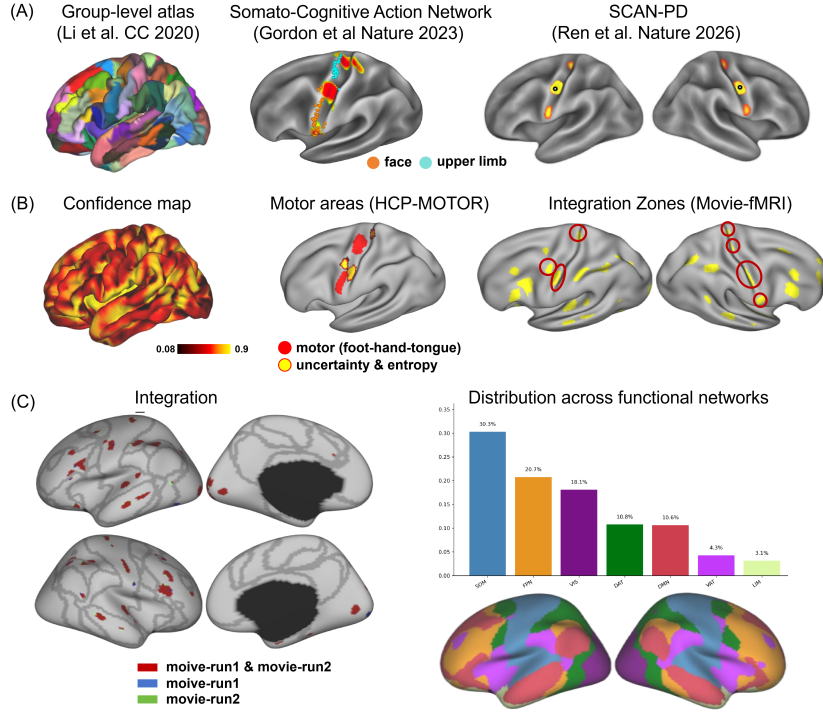


Fig. 3. Functional characterization of multimodal integration zones.

Spatial Localization of SCAN Integration Zones To contextualize entropy-defined integration zones, we compared their spatial distribution with an adolescent group atlas [9], canonical SCAN [3], and SCAN-related circuitry [12] (Fig. 3A). Entropy-defined regions aligned with SCAN territories while remaining spatially separable from classical effector-specific motor representations [11, 13]. At the individual level, high-entropy vertices were positioned adjacent to HCP-MOTOR hand, foot, and tongue anchors but distinct from motor cores (Fig. 3B). These patterns were reproducible across movie halves (Fig. 3C). Network enrichment analysis showed predominant embedding within Sensorimotor, Frontoparietal, and Default Mode systems [15], with limited representation in Visual and Limbic networks.

Multimodal Analysis of SCAN and Auditory Integration Hubs We further examined the functional properties of entropy-defined integration hubs within SCAN and auditory-linguistic territories (Fig. 4). Across both hemispheres, these hubs were consistently located between effector-specific regions and exhibited broader functional connectivity patterns relative to adjacent motor cores (Fig. 4A-B). Meta-analytic decoding associated these regions with heterogeneous motor, perceptual, and cognitive terms, suggesting multi-domain

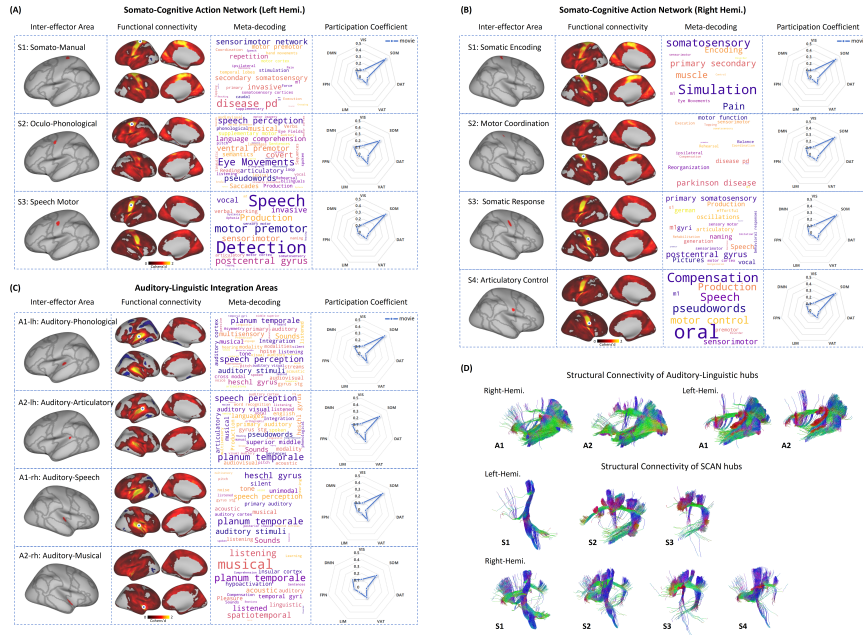


Fig. 4. Multimodal profiling reveals distinct integration hierarchies in SCAN and Auditory-Linguistic hubs.

functional engagement. Participation coefficient analyses demonstrated significantly elevated cross-network embedding compared to neighboring areas, indicating enhanced integrative involvement across sensorimotor and control systems. Auditory-linguistic hubs similarly showed distributed coupling across temporal, parietal, and frontal cortices (Fig. 4C). Structural tractography further revealed that these regions were embedded within long-range association pathways, including fronto-parietal and temporo-frontal connections, supporting their role as anatomically grounded integrative nodes (Fig. 4D).

Integration Zones Show Distinct Connectivity We next examined the spatial and connectivity relationships between entropy-defined integration zones and canonical motor representations (Fig. 5). HCP-MOTOR anchors delineated hand, foot, and tongue territories along the precentral gyrus (Fig. 5A). Entropy-defined integration zones were consistently adjacent to, yet spatially separable from, these effector-specific motor cores, forming interdigitated territories along the motor strip (Fig. 5B). Whole-brain connectivity comparisons between integration seeds and motor anchors (FDR-corrected $p < 0.05$; Fig. 5C) demonstrated that integration zones exhibited significantly more distributed connectivity patterns. Whereas motor anchors showed predominantly focal peri-rolandic coupling, integration zones extended into frontal, parietal, temporal, and cingulo-

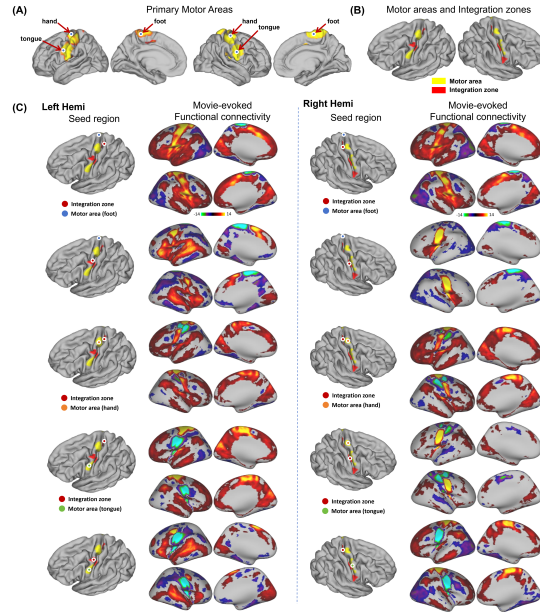


Fig. 5. The SCAN network is spatially interdigitated but functionally distinct from the motor homunculus.

opercular systems, indicating broader large-scale network embedding relative to primary motor regions.

4 Discussion

Developmental Modulation of Integration Hubs We further assessed age-related variation in participation coefficients of entropy-defined SCAN hubs (Fig. 6). Several subdivisions exhibited significant correlations with age across adolescence. In the left hemisphere, S1-S3 showed modest negative associations ($r = -0.143$ to -0.203), while right-hemisphere S1, S3, and S4 demonstrated similar trends ($r = -0.150$ to -0.170). Age-group comparisons confirmed reduced participation in late adolescence for selected hubs. Network-specific analyses (Fig. 6B) revealed differential patterns across systems. For example, S2 showed decreased visual network participation, whereas S3 and right S4 exhibited increased somatomotor coupling. The A2 auditory-prosodic hub demonstrated reduced default mode network engagement. These findings indicate that entropy-defined integration hubs exhibit measurable developmental variation in large-scale network embedding, further supporting their functional relevance.

We developed an uncertainty-aware spatiotemporal graph learning framework for individualized cortical parcellation in the developing brain. In contrast to approaches that rely primarily on static connectivity representations

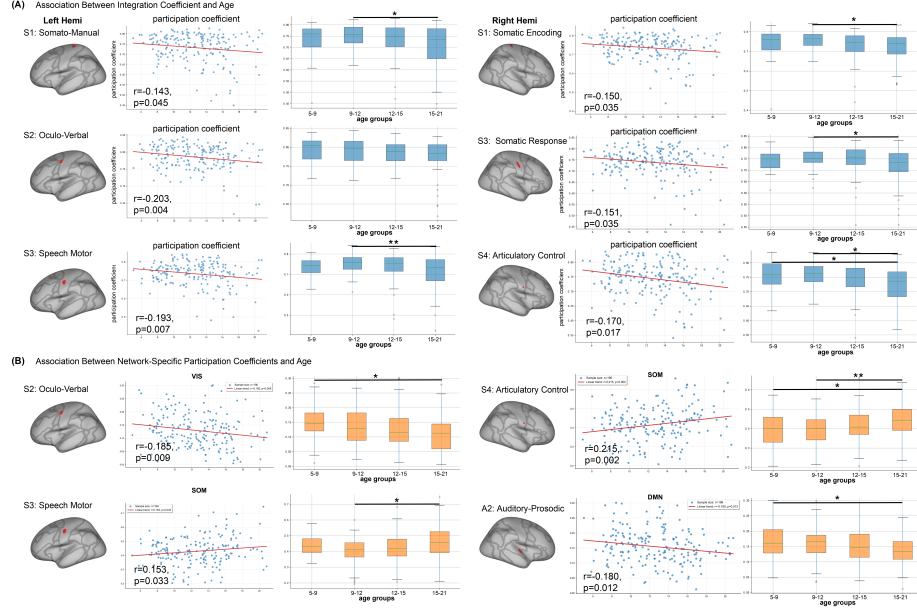


Fig. 6. State-invariant and context-specific maturation of integration zones.

or group-averaged templates [7, 15], our framework explicitly models vertex-wise BOLD dynamics prior to spatial classification. By integrating neighborhood self-attention, dual-channel recurrent encoding, and topology-constrained graph convolution, the model captures temporally informed local interactions while preserving surface topology. This design demonstrates that explicit temporal modeling enhances the robustness and specificity of individualized areal delineation under high inter-subject variability (Fig. 1).

A second contribution lies in the probabilistic formulation. Rather than collapsing predictions into discrete labels, the framework retains vertex-wise class probability distributions to derive entropy-based uncertainty estimates. A mixture-based uncertainty stratification with cross-run validation identified reproducible high-entropy territories at the group level. The inverse relationship between prediction confidence and inter-subject variability aligns with prior demonstrations of individualized cortical organization [4, 8, 10], supporting uncertainty as a principled marker of graded functional differentiation rather than classification noise.

Across analyses, entropy-defined integration zones were prominently located along the dorsoventral axis of the Somato-Cognitive Action Network (SCAN) [3] and adjacent auditory-linguistic systems. These regions were consistently positioned between canonical effector-specific motor representations and exhibited broader large-scale connectivity patterns and elevated cross-network participation relative to motor anchors (Figs. 3–5). The spatial distribution and net-

work embedding of these territories are consistent with previously described inter-effector organization [1], suggesting that temporally informed uncertainty modeling can recover biologically meaningful transitional cortical zones without predefined integration templates.

Developmentally, entropy-defined SCAN hubs exhibited age-related variation in participation profiles, consistent with prior reports of progressive stabilization and increasing individualization of functional networks during adolescence [2, 6] (Fig. 6). These findings indicate that the proposed framework is sensitive not only to spatial organization but also to developmental modulation of large-scale network integration.

Overall, this work advances individualized cortical mapping by integrating temporal dynamics and uncertainty calibration within a unified graph learning architecture. The approach provides a scalable and reproducible strategy for identifying integration territories under conditions of high inter-individual variability and developmental change.

Acknowledgments. This work was partially supported by the STI2030-Major Projects 2021ZD0200200, 2022ZD0211500, the National Natural Science Foundation of China (Grant Nos. 62201519, 62403465).

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Braga, R.M., Buckner, R.L.: Parallel interdigitated distributed networks within the individual estimated by intrinsic functional connectivity. *Neuron* **95**(2), 457–471 (2017)
2. Fair, D.A., Cohen, A.L., Power, J.D., Dosenbach, N.U., Church, J.A., Miezin, F.M., Schlaggar, B.L., Petersen, S.E.: Functional brain networks develop from a “local to distributed” organization. *PLoS computational biology* **5**(5), e1000381 (2009)
3. Gordon, E.M., Chauvin, R.J., Van, A.N., Rajesh, A., Nielsen, A., Newbold, D.J., Lynch, C.J., Seider, N.A., Krimmel, S.R., Scheidter, K.M., et al.: A somato-cognitive action network alternates with effector regions in motor cortex. *Nature* **617**(7960), 351–359 (2023)
4. Gordon, E.M., Laumann, T.O., Gilmore, A.W., Newbold, D.J., Greene, D.J., Berg, J.J., Ortega, M., Hoyt-Drazen, C., Gratton, C., Sun, H., et al.: Precision functional mapping of individual human brains. *Neuron* **95**(4), 791–807 (2017)
5. Graziano, M.S., Taylor, C.S., Moore, T.: Complex movements evoked by microstimulation of precentral cortex. *Neuron* **34**(5), 841–851 (2002)
6. Kaufmann, T., Alnæs, D., Doan, N.T., Brandt, C.L., Andreassen, O.A., Westlye, L.T.: Delayed stabilization and individualization in connectome development are related to psychiatric disorders. *Nature neuroscience* **20**(4), 513–515 (2017)
7. Kong, R., Yang, Q., Gordon, E., Xue, A., Yan, X., Orban, C., Zuo, X.N., Spreng, N., Ge, T., Holmes, A., et al.: Individual-specific areal-level parcellations improve functional connectivity prediction of behavior. *Cerebral cortex* **31**(10), 4477–4500 (2021)

8. Laumann, T.O., Gordon, E.M., Adeyemo, B., Snyder, A.Z., Joo, S.J., Chen, M.Y., Gilmore, A.W., McDermott, K.B., Nelson, S.M., Dosenbach, N.U., et al.: Functional system and areal organization of a highly sampled individual human brain. *Neuron* **87**(3), 657–670 (2015)
9. Li, W., Fan, L., Shi, W., Lu, Y., Li, J., Luo, N., Wang, H., Chu, C., Ma, L., Song, M., et al.: Brainnetome atlas of preadolescent children based on anatomical connectivity profiles. *Cerebral Cortex* **33**(9), 5264–5275 (2023)
10. Mueller, S., Wang, D., Fox, M.D., Yeo, B.T., Sepulcre, J., Sabuncu, M.R., Shafee, R., Lu, J., Liu, H.: Individual variability in functional connectivity architecture of the human brain. *Neuron* **77**(3), 586–595 (2013)
11. Penfield, W., Boldrey, E.: Somatic motor and sensory representation in the cerebral cortex of man as studied by electrical stimulation. *Brain: A journal of neurology* (1937)
12. Ren, J., Zhang, W., Dahmani, L., Gordon, E.M., Li, S., Zhou, Y., Long, Y., Huang, J., Zhu, Y., Guo, N., et al.: Parkinson’s disease as a somato-cognitive action network disorder. *Nature* pp. 1–9 (2026)
13. Schieber, M.H.: Constraints on somatotopic organization in the primary motor cortex. *Journal of neurophysiology* **86**(5), 2125–2143 (2001)
14. Vanderwal, T., Eilbott, J., Castellanos, F.X.: Movies in the magnet: Naturalistic paradigms in developmental functional neuroimaging. *Developmental cognitive neuroscience* **36**, 100600 (2019)
15. Yeo, B.T., Krienen, F.M., Sepulcre, J., Sabuncu, M.R., Lashkari, D., Hollinshead, M., Roffman, J.L., Smoller, J.W., Zöllei, L., Polimeni, J.R., et al.: The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of neurophysiology* (2011)