Attention Modulates the Geometry of Auditory Representations

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Abstract

Attention plays a crucial role in shaping auditory representations, yet its impact on brain space geometry remains unclear. In this study, we investigated how attention modulates auditory object representations using fMRI (n=20). We conducted two experiments: (1) Exp OA, where participants listened to a single auditory object from one of three categories (speech, animal or instrument sounds) (2) Exp 3OA, where an auditory scene comprising three overlapping objects, each from a different category, was presented, with attention directed to one of the objects. We applied principal component analysis (PCA) to reduce data dimensionality and Procrustes analysis to align brain representations across both participants and experiments. Our results demonstrate that in 3OA auditory scenes, attention reorganizes scene geometry by shifting the entire representation toward the representational location of the attended object (as estimated from OA data). These effects were observed across nonprimary auditory regions for all object types and in a broader language network for speech. Our approach shows that key attentional effects emerge when neural data are analyzed in multidimensional brain spaces.

Keywords: attention; object representation; hyperalignment; auditory; brain space geometry

Introduction

In scenes with overlapping sounds, selective attention plays a significant role in separating relevant (attended) sound sources from irrelevant sounds (distractors). Traditional models posit that mechanistically this is achieved by increasing the neural gain of sensory neurons in auditory cortex (AC) processing the attended features, while suppressing those processing unattended features (Schäfer et al., 2018). Yet, in natural scenes the constituent objects can seldom be distinguished based on one feature alone (e.g., pitch). Consequently, it has been suggested that attention increases the gain of neurons processing full auditory objects (Shinn-Cunningham, 2008). Given that it is unfeasible that each object is represented by a single neuron, modern views suggest that object representations emerge from population codes in multidimensional brain spaces (Ebitz & Hayden, 2021). Yet, it has not been tested whether attention modulates such population-coded object representations.

We tested whether selective attention shifts the representation of auditory scenes, comprising three overlapping auditory objects, towards the representational point of the attended object. We conjectured that each auditory object occupies a distinct point in this space and can act as an attractor in the brain space manifold (Ebitz & Hayden, 2021). Attention may dynamically change the manifold geometry, causing the scene's representation to gravitate towards the point corresponding to the attended object.

Methods

We collected fMRI data (n=20) in two experiments. In Experiment OA, participants listened to a single auditory object (duration: 4-7 s) belonging to one of three categories (speech, animal or instrument sounds). In Experiment 3OA, three auditory objects belonging to different categories were presented simultaneously, with participants instructed to attend to one of the objects. Each experiment comprised 4 runs.

Beta estimates were obtained from a general linear model (GLM) including all conditions as separate regressors from preprocessed (fmriprep) and fsaverage-surface projected data (Fischl, 2012). We constructed response matrices X (M × N), where M=18 stimuli (6 objects per category) and N=number of vertices, separately for each subject, experiment and ROI (HCP parcellation; Glasser et al., 2016), and applied hyperalignment (Haxby et al., 2011) (without scaling) across subjects (Fig. 1A). We reduced data dimensionality via Principal Component Analysis (PCA; (Panichello & Buschman, 2021), and aligned PC-scores across experiments using procrustes alignment (Barbosa et al., 2025) (without scaling) at the subject level to ensure comparability across experiments. To quantify differences in representational geometry, we computed Euclidean distances at the object-level between OA object representation points and representations of scenes where the relevant object was either attended (ED1) or a distractor in 3OA (ED2, using the first 3 PCs). To test whether the attended representation was closer than the distractor, we tested Euclidean difference scores using permutation-based paired t-tests at ROI-level (Fig. 1B). We provide our scripts online.[1]

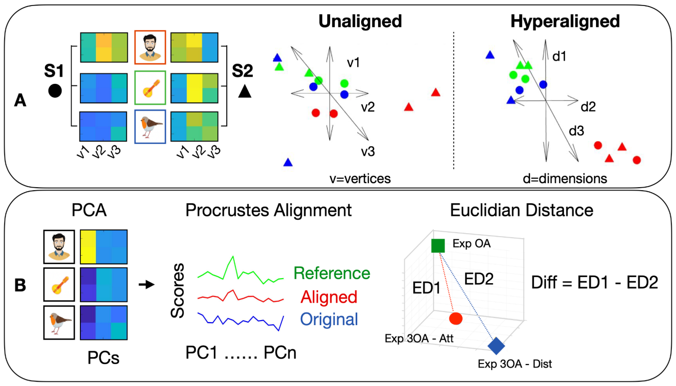

Figure 1: *Brain space geometry analysis pipeline.* A. Hyperalignment of the response matrix (X) across subjects. We illustrate beta values matrices from two subjects and 6 stimuli (2 for each category) and their corresponding geometric representations in a 3-vertex space. Generalized Procrustes Analysis is applied to align subjects to a common representational space, to ensure comparability. B. The aligned data are subjected to PCA to project responses into a lower-dimensional space. PC-scores are aligned across experiments using Procrustes and used to assess the effect of attention on brain representation geometry (Euclidean Distance).

Results

Across categories, attention shifts neural representation of the scenes towards the attended object (brain space locations estimated using OA-data, where each object was presented alone). This effect was observed for all object types in non-primary Auditory Cortex (AC), with the most consistent modulations observed in area A5 (Fig. 2, bottom left) and in the Superior Temporal Sulcus (STS). For speech, this modulation extends further into the left frontal lobe, including the Inferior Frontal Gyrus (IFG) (Fig. 2, bottom right).

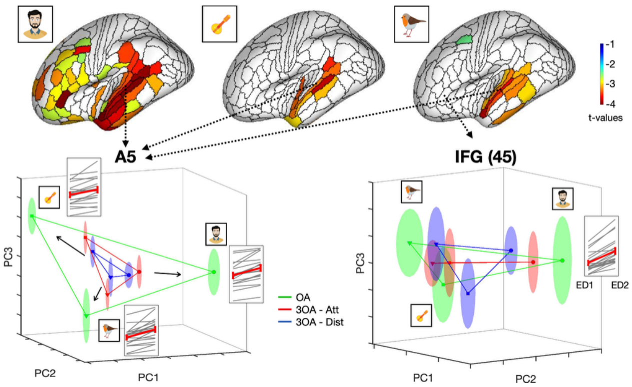

Figure 2. *Attentional shift of brain spaces.* Top: Whole-brain map showing where attention shifts brain representations toward attended objects (colors: FDR corrected t-values). Bottom: Spatial representation of the centroid for each category, with ± standard error (SEM) defined by the absolute distance between each object and the centroid of its category. In the panel of A5, black arrows indicate the expected direction of the attentional shift. For each significant effect, differences in Euclidean distance are shown at the subject level (grey lines), along with the mean and SEM (red line).

Discussion

As expected, scene representations were attracted towards attended objects in brain spaces, i.e., attention transformed scene representations towards solely representing the attended object. In non-primary AC regions this was evident for all categories, indicating that single regions may represent multiple objects, with attention differentiating relevant objects from distractors by routing them along distinct paths. For speech, this effect extended to approximately the whole speech processing network (Fedorenko et al., 2024), while for instrument and animal sounds the effect was confined to auditory regions and areas supporting multimodal representations, such as the Anterior Temporal Lobe (ATL; Ralph et al., 2017).

Future analyses could focus on dissecting this effect into its components: (1) general categorical attraction – i.e., scenes with attended animal objects gravitate towards animal representations; and (2) object specific attraction – i.e., attending to dogs attracts scene representations closer to that of dogs than those of other animal sounds (e.g., birds). Our results highlight that key top-down mechanisms emerge only when considering brain space geometry.

[1] https://github.com/neural-review2025/SoundScapes

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References

Barbosa, J., Nejatbakhsh, A., Duong, L., Harvey, S. E., Brincat, S. L., Siegel, M., Miller, E. K., & Williams, A. H. (2025). Quantifying differences in neural population activity with shape metrics. In *bioRxiv*. https://doi.org/10.1101/2025.01.10.632411

Ebitz, R. B., & Hayden, B. Y. (2021). The population doctrine in cognitive neuroscience. In *arXiv [q-bio.NC]*. arXiv. http://arxiv.org/abs/2104.00145

Fedorenko, E., Ivanova, A. A., & Regev, T. I. (2024). The language network as a natural kind within the broader landscape of the human brain. *Nature Reviews. Neuroscience*, *25*(5), 289–312. https://doi.org/10.1038/s41583-024-00802-4

Fischl, B. (2012). FreeSurfer. *NeuroImage*, *62*(2), 774–781. https://doi.org/10.1016/j.neuroimage.2012.01.021

Glasser, M. F., Coalson, T. S., Robinson, E. C., Hacker, C. D., Harwell, J., Yacoub, E., Ugurbil, K., Andersson, J., Beckmann, C. F., Jenkinson, M., Smith, S. M., & Van Essen, D. C. (2016). A multi-modal parcellation of human cerebral cortex. *Nature*, *536*(7615), 171–178. https://doi.org/10.1038/nature18933

Haxby, J. V., Guntupalli, J. S., Connolly, A. C., Halchenko, Y. O., Conroy, B. R., Gobbini, M. I., Hanke, M., & Ramadge, P. J. (2011). A common, high-dimensional model of the representational space in human ventral temporal cortex. *Neuron*, *72*(2), 404–416. https://doi.org/10.1016/j.neuron.2011.08.026

Panichello, M. F., & Buschman, T. J. (2021). Shared mechanisms underlie the control of working memory and attention. *Nature*, *592*(7855), 601–605. https://doi.org/10.1038/s41586-021-03390-w

Ralph, M. A. L., Jefferies, E., Patterson, K., & Rogers, T. T. (2017). The neural and computational bases of semantic cognition. *Nature Reviews. Neuroscience*, *18*(1), 42–55. https://doi.org/10.1038/nrn.2016.150

Schäfer, P. J., Corona-Strauss, F. I., Hannemann, R., Hillyard, S. A., & Strauss, D. J. (2018). Testing the limits of the stimulus reconstruction approach: Auditory attention decoding in a four-speaker free field environment. *Trends in Hearing*, *22*, 233121651881660. https://doi.org/10.1177/2331216518816600

Shinn-Cunningham, B. G. (2008). Object-based auditory and visual attention. *Trends in Cognitive Sciences*, *12*(5), 182–186. https://doi.org/10.1016/j.tics.2008.02.003