A high-density diffuse optical tomography dataset of naturalistic viewing

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Abstract

Traditional laboratory tasks offer tight experimental control but lack the richness of our everyday human experience. As a result many cognitive neuroscientists have been motivated to adopt experimental paradigms that are more natural, such as stories and movies. Here we describe data collected from 58 healthy adult participants (aged 18–76 years) who viewed 10 minutes of a movie (*The Good, the Bad, and the Ugly*, 1966). Most (36) participants viewed the clip more than once, resulting in 106 sessions of data. Cortical responses were mapped using high-density diffuse optical tomography (first- through fourth nearest neighbor separations of 1.3, 3.0, 3.9, and 4.7 cm), covering large portions of superficial occipital, temporal, parietal, and frontal lobes. Consistency of measured activity across subjects was quantified using intersubject correlation analysis. Data are provided in both channel format (SNIRF) and projected to standard space (NIfTI), using an atlas-based light model. These data are suitable for methods exploration as well as investigating a wide variety of cognitive phenomena.

Background & Summary

Most cognitive neuroscientists are interested in how human brains navigate the real world. To do so, we frequently create tightly-controlled laboratory paradigms intended to isolate one or more aspects of sensory or cognitive processing. We hope that the findings from these purposefully artificial experiments will generalize to real-world scenarios. However, is such an assumption justified? To answer this question, cognitive neuroscience has been increasingly moving towards the use of naturalistic stimuli (Zaki and Ochsner, 2009; Sonkusare et al., 2019; Nastase et al., 2020; Finn et al., 2022).

For over 20 years, researchers using fMRI have explored the use of movies to provide rich stimulation for research participants including newborns , children (Richardson et al., 2018; Yates et al., 2021; Tansey et al., 2023), healthy adults (Zacks et al., 2001; Hasson et al., 2004; Naci et al., 2014; Chen et al., 2017; Aliko et al., 2020; Caldinelli and Cusack, 2022), and numerous other populations (Loiotile et al., 2019; Lyons et al., 2020; Musz et al., 2022; Yao et al., 2022). Although not completely naturalistic, movies convey complex auditory and visual information covering a range of sensory, cognitive, and linguistic domains. Movies therefore provide researchers the opportunity to study processing that more closely mimics everyday experience than standard laboratory tasks. Additionally, the ability to concurrently address multiple domains of sensory and cognitive processing may make movies a more efficient way to collect data than traditional cognitive psychology paradigms. For example, 10 minutes of movie data collection might replace 30 minutes of domain-specific data collection (e.g., 10 minutes of an auditory task, 10 minutes of a visual task, 10 minutes of a language task).

Optical neuroimaging, particularly functional near infrared spectroscopy (fNIRS), offers many advantages for studying human brain function. First, it is acoustically silent, avoiding the auditory confounds present in fMRI (Peelle, 2014). Second, implanted medical devices are not contraindicated, meaning optical imaging can be used on people with implanted medical devices, such as cochlear implants (Saliba et al., 2016; Sherafati et al., 2022) or implanted electrodes used for deep brain stimulation (Eggebrecht et al., 2014). Finally, fNIRS facilitates real-world applications including imaging during face-to-face interaction (Hirsch et al., 2020). These advantages make fNIRS well suited for studying cognition in context (Thomas, 2023) that includes social interaction (Dingemanse et al., 2023).

Traditionally, drawbacks associated with fNIRS include limited coverage of the cortex, uneven sensitivity over the field of view, and lack of depth information necessary for removing superficial (i.e., non-brain) hemodynamic components. These challenges motivated the development of high-density diffuse optical tomography (HD-DOT), in which a lattice of closely-spaced sources and detectors provides homogenous sensitivity and spatial resolution comparable to that obtained in fMRI (**Figure 1**) (Eggebrecht et al., 2014).

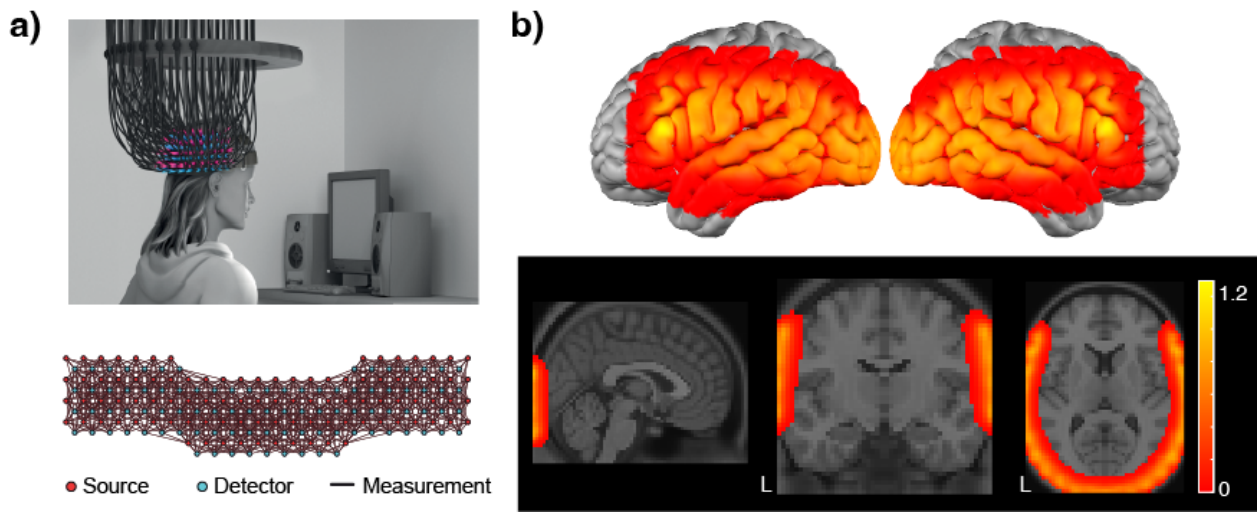

Figure 1. a) Illustration of HD-DOT cap and optode arrangement (see Eggebrecht et al., 2014 for details). **b)** Illustration of field of view in the reconstructed images.

Here, we present data collected using custom high-density optical tomography during movie-viewing. Although the use of movies in HD-DOT has been previously explored (Fishell et al., 2019), our hope is that by making the current data available we will facilitate methodological and theoretical advances related to naturalistic stimulation. These include identification of quality control metrics, how to best handle estimated motion, and optimal methods for modeling quasi-continuous variables.

Method

Participants

Data from 58 participants are included in the data set, ranging in age from 18–76 years (M = 23; F = 35; mean age = 31); self-reported handedness (right = 55, left = 2, ambidextrous = 1). Forty nine of the participants reported English as the first language they learned. Participants were recruited from the Washington University in Saint Louis community. In addition, participants reported to have normal vision and hearing and no known history of neurological disorders. All participants gave written informed consent prior to the experiment session, which was approved by and carried out in accordance with the Human Research Protection Office at Washington University.

Stimulus

The stimulus was a 10-minute clip taken from *The Good, the Bad, and the Ugly* (1966), a movie previously used in fMRI (Hasson et al., 2004) and HD-DOT (Fishell et al., 2019). All participants viewed between 16 minutes and 48 sec and 26 minutes 48 sec. A subset of the participants viewed a longer clip; in this case, their data were truncated to 10 minutes so that all participants had the same amount of data covering an identical portion of the movie. Copyright restrictions preclude openly sharing the stimulus but guidance is available on request from the corresponding author. We did not

systematically document whether participants had previously viewed the selected clip; anecdotally, most participants reported being unfamiliar with the movie.

The same movie clip was used in several projects between 2012–2022 and thus was presented along with various other tasks, including auditory, visual, motor, language, and collection of resting state data. Analyses including 7 of these participants have been published previously (Fishell et al., 2019) but none of the data is included in a public data set.

Procedure

Participants were seated on a comfortable chair in an acoustically isolated room facing an LCD screen located 76 cm from them, at approximately eye level, which displayed the movie. The soundtrack was presented through two speakers located approximately 150 cm away at about ± 21° from the subjects' ears. The sound level was approximately 65 dBA but not calibrated. The HD-DOT cap was fitted to the subject's head to maximize optode-scalp coupling, assessed via real-time coupling coefficient readouts using in-house software. The movie was presented using Psychophysics Toolbox 3 (Brainard, 1997) (RRID:SCR_002881) in MATLAB.

Data acquisition

Data was acquired using two different continuous wave HD-DOT caps. The first cap had 96 sources and 92 detectors (LED) (shining 750 nm and 850 nm near-infrared light) (Eggebrecht et al., 2014) and was used in 9 (of total 58) participants. The second cap was built by attaching an additional pad on top of the previous cap and had 128 sources and 125 detectors (Laser diode) (shining 685 nm and 830 nm near-infrared light) and was used in the remaining 49 participants. Source-detector pairs were arranged on both caps to enable first- through fourth nearest neighbor separations of 1.3, 3.0, 3.9, and 4.7 cm, respectively. Our in-house software controlled temporal, frequency, and spatial encoding patterns which achieved an overall framerate of 10 Hz.

Full measurement sets are available in the raw data formats (NeuroDOT and snirf). In order to make the analyses in this paper consistent, we have removed all the measurements from the additional motor pad in 49 participants that were scanned using the bigger cap to contain the same 96 sources and 92 detectors as the other subjects in the preprocessed data formats (nii and BIDS) and all the analyses presented in this paper.

Data processing

Data processing is schematically illustrated in **Figure 2**. Data preprocessing was done using the NeuroDOT toolbox (https://www.nitrc.org/projects/neurodot) based on the principles of modeling light emission, diffusion, and detection through the head (Eggebrecht and Culver, 2019; Sherafati et al., 2022). Data processing steps included taking the log-mean ratio of the light levels for each time-point and the temporal mean across the run (as a baseline value). This step was followed by excluding any source-detector measurement that had a temporal standard deviation of 7.5% in the least-noisy 60 sec (lowest mean GVTD; Sherafati et al., 2020) of each run or higher to exclude any noisy measurements due to poor optode-scalp coupling or movement. Due to low SNR, we did not use the measurements beyond second nearest neighbors. The

measurements were then high-pass filtered (0.02 Hz cutoff) to remove low-frequency drift. We then estimated and regressed the global superficial signal as the average of all first nearest neighbor measurements (1.3 cm source-detector pair separation) (Gregg et al., 2010). Following that, data were low-pass filtered to 0.5 Hz cutoff to remove cardiac oscillations. These frequencies were chosen in all previous studies that were published using the existing HD-DOT devices and are consistent with best practices (Yücel et al., 2021). Data were then down-sampled from 10 to 1 Hz and then used for image reconstruction.

We then computed a forward model of light propagation based on the two wavelengths used for each device on an anatomical atlas including the non-uniform tissue structures: scalp, skull, CSF, gray matter, and white matter (Ferradal et al., 2014). The resulting sensitivity matrix was then inverted for calculating the relative changes in absorption at the two wavelengths via reconstruction using Tikhonov regularization and spatially variant regularization (Eggebrecht et al., 2014). Relative changes in oxygenated, deoxygenated, and total hemoglobin (ΔHbO, HbR, ΔHbT) were then computed using the absorption and extinction coefficients of oxygenated and deoxygenated hemoglobin at the two wavelengths. We resampled all data to a 3 × 3 × 3 mm standard atlas using a linear affine transformation.

The preprocessed data were then converted to the NIfTI file format for analysis and sharing purposes. Intersubject correlation analysis was performed using the automatic analysis (aa) environment (Cusack et al., 2015), version 5.8. Additionally, the *ndot2snirf* function in NeuroDOT was used to convert the raw data to SNIRF file format followed by *snirf2bids* function to generate other necessary metadata files to satisfy the BIDS specification for NIRS (Gorgolewski et al., 2016; Tucker et al., 2023). In addition to using these standard functions, the NIfTI files were cropped to align with the actual start and end points of the movie stimulus.

Data Records

The data records are organized following the Brain Imaging Data Structure (BIDS standard (Gorgolewski et al., 2016) and available as dataset ds004569 on OpenNeuro (Markiewicz et al., 2021), and listed on OpenfNIRS.org.

Technical Validation

Data quality

To quantify data quality across sessions we focused on two measures intended to capture effects of participant motion and light levels (**Figure 3**). Because we do not have objective measures of motion (e.g., photometry or accelerometers), we rely on a signal-based proxy for motion: global variance of temporal derivatives (GVTD) (Sherafati et al., 2020). GVTD is conceptually similar to the DVARS measure sometimes used in fMRI (Smyser et al., 2011; Power et al., 2012).

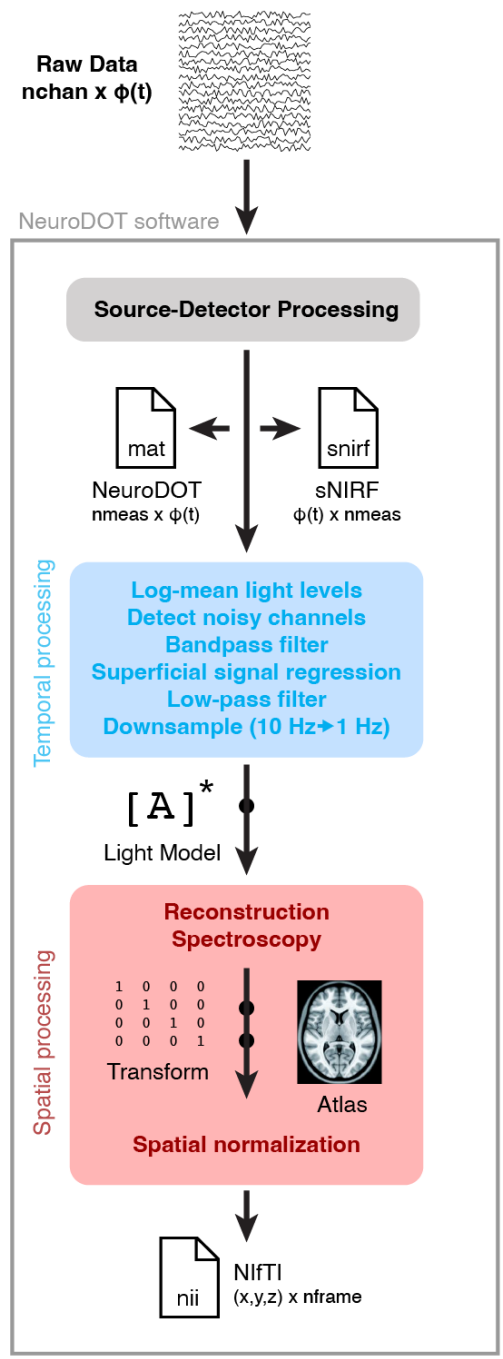

Figure 2. Schematic of data processing and file formats. The data are provided in three different formats: SNIRF, NeuroDOT, and NIfTI.

We used the heartbeat (pulse) signal-to-noise ratio (SNR) as an indicator of detecting physiological signal in the data. The pulse SNR was calculated as the proportion of the pulse power (based on the peak FFT magnitudes in the 0.5–2 Hz window) divided by a noise floor (based on the FFT magnitudes in the 0.5–1 Hz window).

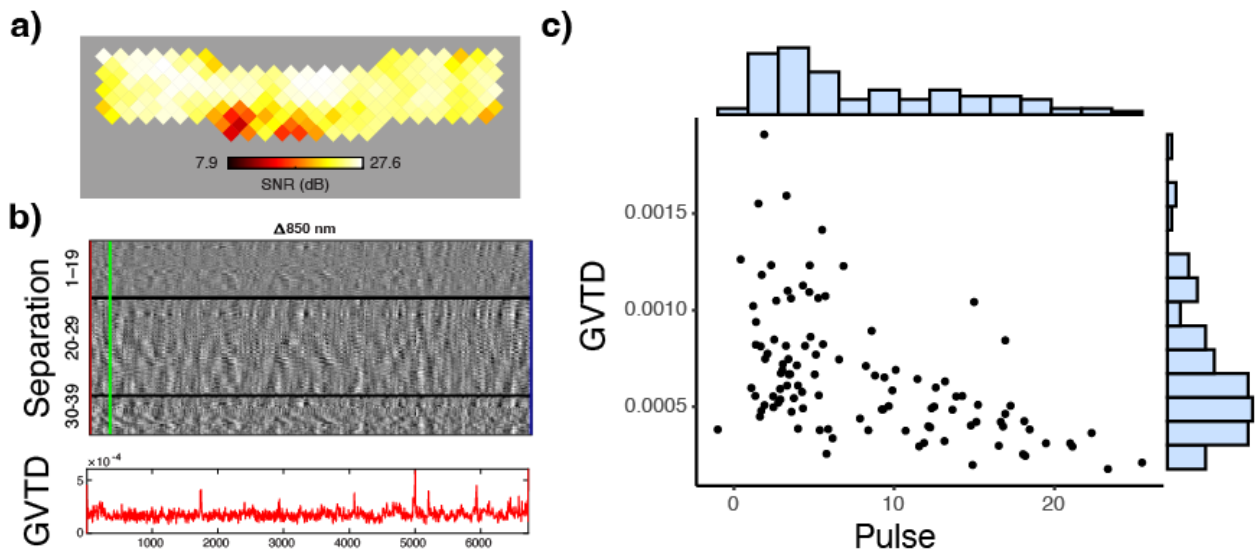

Figure 3. Quality control measures. **a)** Mean light levels over the cap for a sample participant (850 nm light). **b)** *Top:* example temporal derivative time traces from source detector distances between 1–19 mm, 20–29 mm, and 30–40 mm respectively, for 850 nm light in the same sample participant; *Bottom:* GVTD over the same time period. **c)** Scatter plot of GVTD (proxy for motion) and pulse levels for all sessions.

Intersubject correlation analyses

In an intersubject correlation analysis, the similarity of time courses is computed for the same voxel in each pair of participants; averaging these values provides an average intersubject correlation value for every voxel of the brain (Nastase et al., 2019). Numerous studies have used intersubject correlation analysis to identify regions of the brain which show similar patterns of activity across a group of participants. For movie viewing, these values are typically higher in sensory regions (e.g, visual cortex and auditory cortex) than regions associated with complex linguistic or executive processing (Hasson et al., 2004; Visconti di Oleggio Castello et al., 2020). One benefit of intersubject correlation analysis is that it is sensitive to shifts in the timing of activity across participants. Thus, demonstrating reasonable intersubject correlation values in sensory regions suggests the time courses across participants are correctly temporally aligned.

As part of our technical validation, we therefore performed an intersubject correlation analysis (**Figure 4a**). Because not all participants had multiple sessions of movie data, we restricted our analysis to the session with the highest pulse SNR from each participant. The signal average was subtracted from each frame and a Pearson

correlation coefficient was then computed voxel-wise using the corrected data for all pairs of subjects. We see the highest values in auditory and visual cortices, broadly consistent with prior studies in both fMRI (Hasson et al., 2004) and HD-DOT (Fishell et al., 2019).

We then placed participants into one of three groups based on pulse amplitude measured in the optical signal (low group: 3.0 < pulse ≤ 6.0; med: 6.0 < pulse ≤ 14.5; high: 14.5 < pulse < 25.5). As shown in **Figure 4b**, we observed that r values were notably higher in subjects in the high pulse amplitude group compared to those in the medium and low groups, supporting our use of pulse amplitude as a quality control measure.

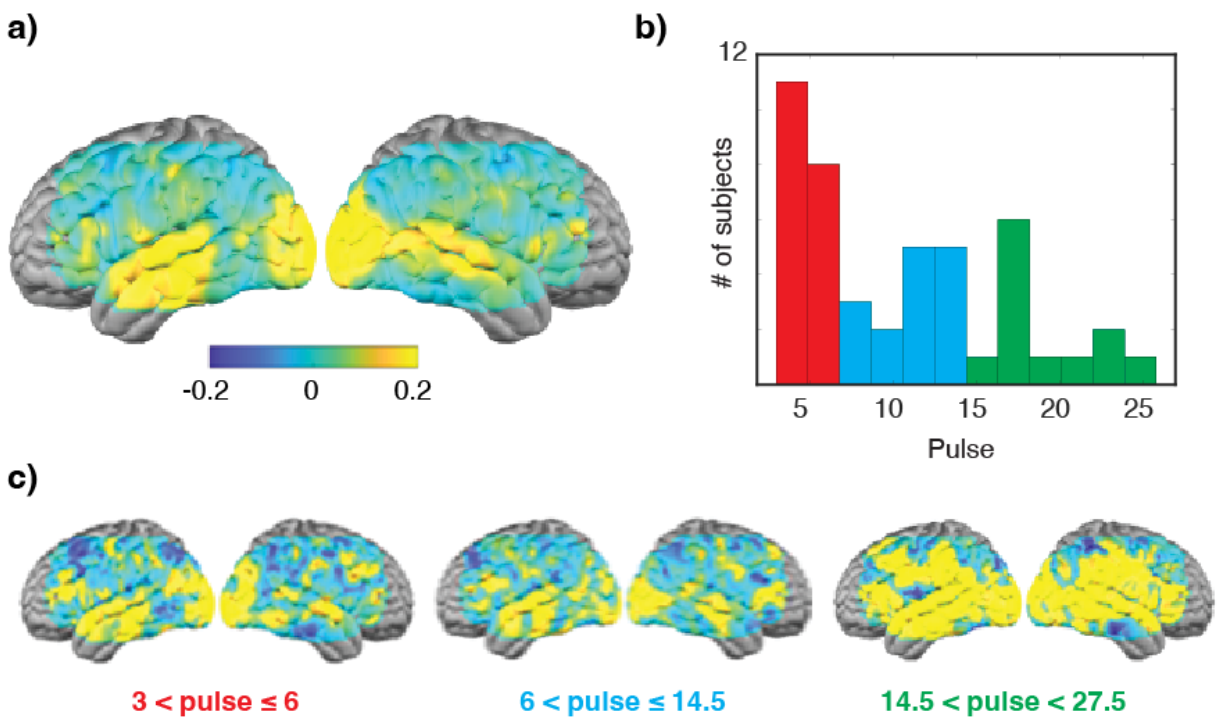

Figure 4. Intersubject correlation analysis. **a)** Correlation map shows the average pairwise correlation across all subjects. Maximum r-values are observed in sensory areas. The SNR in these subjects, as quantified by pulse amplitude, ranged from approximately 3 to 25. **b)** A histogram of pulse values, and used to separate subjects into low (red), medium (blue), and high (green) SNR groups. **c)** Correlation maps obtained for subjects grouped by SNR. High correlations extend beyond sensory areas in the highest SNR group.

Code Availability

Code used for technical validation is available from http://github.com/jpeelle/GBUDOT.

Acknowledgments

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Author Contributions

J.E.P. conceived of the data sharing effort. A.F., A.S., A.B., M.M., and C.H.L. collected the data. E.S., A.B., and A.S. oversaw data conversion and organization. A.B., A.S., M.S.J. completed preprocessing and quality control analyses. M.S.J. conducted the intersubject correlation analyses. The manuscript was drafted by J.E.P., A.S., A.B., and M.S.J., and critically reviewed by all authors. J.E.P., J.P.C., A.T.E., and T.H. obtained funding.

Competing Interests

The authors declare no competing interests.

References

Aliko S, Huang J, Gheorghiu F, Meliss S, Skipper JI (2020) A naturalistic neuroimaging database for understanding the brain using ecological stimuli. Sci Data 7:347.

Brainard DH (1997) The Psychophysics Toolbox. Spat Vis 10:433–436.

Caldinelli C, Cusack R (2022) The fronto-parietal network is not a flexible hub during naturalistic cognition. Hum Brain Mapp 43:750–759.

Chen J, Leong YC, Honey CJ, Yong CH, Norman KA, Hasson U (2017) Shared memories reveal shared structure in neural activity across individuals. Nat Neurosci 20:115–125.

Cusack R, Vicente-Grabovetsky A, Mitchell DJ, Wild CJ, Auer T, Linke AC, Peelle JE (2015) Automatic analysis (aa): Efficient neuroimaging workflows and parallel processing using Matlab and XML. Front Neuroinform 8:90.

Dingemanse M et al. (2023) Beyond Single-Mindedness: A Figure-Ground Reversal for the Cognitive Sciences. Cogn Sci 47:e13230.

Eggebrecht AT, Culver JP (2019) NeuroDOT: an extensible Matlab toolbox for streamlined optical functional mapping. In: Diffuse Optical Spectroscopy and Imaging VII, pp 110740M. International Society for Optics and Photonics.

Eggebrecht AT, Ferradal SL, Robichaux-Viehoever A, Hassanpour MS, Dehghani H, Snyder AZ, Hershey T, Culver JP (2014) Mapping distributed brain function and networks with diffuse optical tomography. Nat Photonics 8:448–454.

Finn ES, Glerean E, Hasson U, Vanderwal T (2022) Naturalistic imaging: The use of ecologically valid conditions to study brain function. Neuroimage 247:118776.

Fishell AK, Burns-Yocum TM, Bergonzi KM, Eggebrecht AT, Culver JP (2019) Mapping brain function during naturalistic viewing using high-density diffuse optical tomography. Sci Rep 9:11115.

Gorgolewski KJ et al. (2016) The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments. Sci Data 3:160044.

Gregg NM, White BR, Zeff BW, Berger AJ, Culver JP (2010) Brain specificity of diffuse optical imaging: improvements from superficial signal regression and tomography. Front Neuroenergetics 2 Available at: http://dx.doi.org/10.3389/fnene.2010.00014.

Hasson U, Nir Y, Levy I, Fuhrmann G, Malach R (2004) Intersubject synchronization of cortical activity during natural vision. Science 303:1634–1640.

Hirsch J, Tiede M, Zhang X, Noah JA, Salama-Manteau A, Biriotti M (2020) Interpersonal Agreement and Disagreement During Face-to-Face Dialogue: An fNIRS Investigation. Front Hum Neurosci 14:606397.

Loiotile RE, Cusack R, Bedny M (2019) Naturalistic Audio-Movies and Narrative Synchronize "Visual" Cortices across Congenitally Blind But Not Sighted Individuals. J Neurosci 39:8940–8948.

Lyons KM, Stevenson RA, Owen AM, Stojanoski B (2020) Examining the relationship between measures of autistic traits and neural synchrony during movies in children with and without autism. Neuroimage Clin 28:102477.

Markiewicz CJ, Gorgolewski KJ, Feingold F, Blair R, Halchenko YO, Miller E, Hardcastle N, Wexler J, Esteban O, Goncavles M, Jwa A, Poldrack R (2021) The OpenNeuro resource for sharing of neuroscience data. Elife 10:e71774.

Musz E, Loiotile R, Chen J, Cusack R, Bedny M (2022) Naturalistic stimuli reveal a sensitive period in cross modal responses of visual cortex: Evidence from adult-onset blindness. Neuropsychologia 172:108277.

Naci L, Cusack R, Anello M, Owen AM (2014) A common neural code for similar conscious experiences in different individuals. Proc Natl Acad Sci U S A 111:14277–14282.

Nastase SA, Gazzola V, Hasson U, Keysers C (2019) Measuring shared responses across subjects using intersubject correlation. Soc Cogn Affect Neurosci 14:667–685.

Nastase SA, Goldstein A, Hasson U (2020) Keep it real: rethinking the primacy of experimental control in cognitive neuroscience. Neuroimage 222:117254.

Peelle JE (2014) Methodological challenges and solutions in auditory functional magnetic resonance imaging. Front Neurosci 8:253.

Power JD, Barnes KA, Snyder AZ, Schlaggar BL, Petersen SE (2012) Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. Neuroimage 59:2142–2154.

Richardson H, Lisandrelli G, Riobueno-Naylor A, Saxe R (2018) Development of the social brain from age three to twelve years. Nat Commun 9:1027.

Saliba J, Bortfeld H, Levitin DJ, Oghalai JS (2016) Functional near-infrared spectroscopy for neuroimaging in cochlear implant recipients. Hear Res 338:64–75.

Sherafati A, Dwyer N, Bajracharya A, Hassanpour MS, Eggebrecht AT, Firszt JB, Culver JP, Peelle JE (2022) Prefrontal cortex supports speech perception in listeners with cochlear implants. Elife 11 Available at: http://dx.doi.org/10.7554/eLife.75323.

Sherafati A, Snyder AZ, Eggebrecht AT, Bergonzi KM, Burns-Yocum TM, Lugar HM, Ferradal SL, Robichaux-Viehoever A, Smyser CD, Palanca BJ, Hershey T, Culver JP (2020) Global motion detection and censoring in high-density diffuse optical tomography. Hum Brain Mapp Available at: http://dx.doi.org/10.1002/hbm.25111.

Smyser CD, Snyder AZ, Neil JJ (2011) Functional connectivity MRI in infants: exploration of the functional organization of the developing brain. Neuroimage 56:1437–1452.

Sonkusare S, Breakspear M, Guo C (2019) Naturalistic Stimuli in Neuroscience: Critically Acclaimed. Trends Cogn Sci 23:699–714.

Tansey R, Graff K, Rohr CS, Dimond D, Ip A, Yin S, Dewey D, Bray S (2023) Functional MRI responses to naturalistic stimuli are increasingly typical across early childhood. Dev Cogn Neurosci 62:101268.

Thomas AK (2023) Studying cognition in context to identify universal principles. Nature Reviews Psychology 2:453–454.

Tucker S, Dubb J, Kura S, von Lühmann A, Franke R, Horschig JM, Powell S, Oostenveld R, Lührs M, Delaire É, Aghajan ZM, Yun H, Yücel MA, Fang Q, Huppert TJ, Frederick BB, Pollonini L, Boas D, Luke R (2023) Introduction to the shared near infrared spectroscopy format. Neurophotonics 10:013507.

Visconti di Oleggio Castello M, Chauhan V, Jiahui G, Gobbini MI (2020) An fMRI dataset in response to “The Grand Budapest Hotel”, a socially-rich, naturalistic movie. Scientific Data 7:1–9.

Yao S, Rigolo L, Yang F, Vangel MG, Wang H, Golby AJ, Liebenthal E, Tie Y (2022) Movie-watching fMRI for presurgical language mapping in patients with brain tumour. J Neurol Neurosurg Psychiatry 93:220–221.

Yates TS, Ellis CT, Turk-Browne NB (2021) Emergence and organization of adult brain function throughout child development. Neuroimage 226:117606.

Yücel MA et al. (2021) Best practices for fNIRS publications. Neurophotonics 8:012101.

Zacks JM, Braver TS, Sheridan MA, Donaldson DI, Snyder AZ, Ollinger JM, Buckner RL, Raichle ME (2001) Human brain activity time-locked to perceptual event boundaries. Nat Neurosci 4:651–655.

Zaki J, Ochsner K (2009) The need for a cognitive neuroscience of naturalistic social cognition. Ann N Y Acad Sci 1167:16–30.