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Inter-subject synchronization of brain responses during movie watching

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Abstract

The effect of shared exposure to naturalistic stimuli on the synchronization of brain activity has been investigated in previous literature. Increased synchronization has been found in several brain regions with exposure to the same movie. The parahippocampal place area (PPA) is known to respond particularly to places and scenes. This study focuses on this brain area and examines whether subjects build up more shared representations of recurring location motives in the PPA when they watch the same movie. To quantify the degree to which subjects create a shared representation, we analyze the progression of inter-subject correlation of brain activity in the PPA for the duration of the movie. We show that repeated exposure to movie locations increases synchronization between subjects during these specific locations, while overall synchronization stays relatively consistent during the whole movie.

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1. Introduction

We continuously receive complex and dynamic information from the world around us. Categorizing all this information into discrete and meaningful concepts requires the creation and adaptation of internal models. When the same stimuli are experienced by multiple individuals, they may give rise to internal representations that are similar between those individuals. Support for this idea is given by previous research (Geerligs and Campbell 2018) that found increased synchronization of brain activity between subjects watching the same movie. This increase in synchronization could be explained by the build-up of similar representations of movie elements.

1.1. Naturalistic stimuli

A lot of research in neuroscience involves the use of brief, simple, and mostly static stimuli because these are easy to control and can result in clear brain signals. However, humans do not encounter these types of stimuli in daily life, which involves a continuous flow of ever-changing information. This highlights a problem in most research done on human brain activity involving stimuli; there is a lack of ecological validity in lab experiments because of a gap with real-life experiences. The use of naturalistic stimuli has seen a relatively recent growth in use in neuroscience, in particular the use of auditory and visual narratives such as movies (Willems et al. 2020).

People often share the same environments in daily life. For example, when two people start living together, they will start sharing a lot more stimuli from their environment compared to before. The same thing happens when people watch a movie for the first time: They share the same virtual environments in the movie through visual and auditory stimuli.

1.2. Brain activity synchronization

Hasson et al. (2004) studied the degree to which brains synchronize when subjects watch half an hour of a movie. They found a significant level of voxel-to-voxel synchronization between these individuals in the primary and secondary visual cortices and association cortices. Later research that looked at the effect of age on the synchronization of brain activity during movie watching has found an increase in inter-subject synchrony over time in the medial prefrontal cortex (mPFC), the frontoparietal control network (FPCN), and the medial temporal lobes (MTL), regardless of age (Geerligs and Campbell, 2018). These studies suggest that subjects indeed process the movie stimulus in a similar way and that this effect seems to enhance over time in at least some brain areas.

1.3. Stable patterns of brain activity

Oetringer et al. (2022) found that stable patterns of brain activity in the parahippocampal place area (PPA) were found to partially align with changes in locations in a movie. Baldassano et al. (2017) used a data-driven approach and found event boundaries as shifts between stable patterns of brain activity. It was revealed that there exists a nested hierarchy of event segmentation with sensory regions showing short events and high-order areas showing longer events. If we consider these stable patterns of brain activity to represent separate real-life events, we suggest that we can also look at changes in synchronization of brain activity in discrete time segments, as opposed to continuous change.

We take this discrete approach and demonstrate whether human subjects show a build-up of more shared representations of location segments in a movie in the PPA specifically, as it is considered to be involved in place and scene processing (Epstein and Kanwisher, 1998; Epstein, 2008). We hypothesized that, just like the brain regions studied by Geerligs & Campbell (2018), the PPA shows an increase in synchronization as the movie progresses, and that synchrony correlates further with repeated exposure to movie locations as subjects get more familiar with these environments. This leads to the following research questions:

- Does synchronization between subjects correlate with cumulative movie watch time?
- Does repeated exposure to places lead to increased synchronization between subjects in the PPA?

2. Methods

2.1. Data

2.1.1. Forrest Gump fMRI data

For this research, we used a hyperaligned derivative (Oetringer et al., 2022) of a StudyForrest dataset, which is freely available (Liu et al. 2019). In their work, they denoised the original fMRI data from Hanke et al. (2016), improving the signal-to-noise ratio and providing higher sensitivity in inter-subject correlation (ISC) analysis, which is what we used. The dataset contains 3 Tesla blood oxygen level-dependent (BOLD) fMRI data with a spatial resolution of 3.0×3.0×3.0 mm per voxel. The data was collected from 15 participants (age 19–30, mean 22.4, 10 females) who watched an edited, 2-hour version of the movie Forrest Gump. These participants are a subset of the 20 participants from the original StudyForrest dataset, which listened to an audio version of the movie (Hanke et al., 2014). We will refer to these participants by their original numbering, which means they are not numbered from 1 to 15. The movie was presented chronologically as eight segments during two sessions, four segments per session. In between sessions, each participant took a break of approximately 10 minutes. The fMRI volumes were taken with a 2 s repetition time (TR), resulting in 3599 volumes for the eight runs combined.

2.1.2. Hyperaligned fMRI data

Shared representations across participants of incoming stimuli are encoded in idiosyncratic topographies, which makes studying the synchronization of raw fMRI data difficult. Correcting for these idiosyncrasies through a method called hyperalignment helps us better discover shared representations across subjects (Haxby et al, 2020). This method creates a common high-dimensional information space where pattern vectors for neural responses and connectivities are projected into, such that neural representations from subjects are functionally aligned to each other.

For this study, we used the data from the work of Oetringer et al. (2022), where they preprocessed the fMRI data from Liu et al. (2019), applied hyperalignment, and transformed it into MNI space. The hyperalignment was performed on the 4th run in the movie, and they applied the resulting mapping to all runs.

2.1.3. Location annotations

To relate our measurements to movie locations, we used annotations that were provided by Häusler et al. (2016) for the Forrest Gump movie. For each run, the relative onsets and durations of locations depicted in the movie are coded with three levels of detail; major location, setting, and locale. Multiple consecutive scenes can have the same location labels, but different additional properties. For this research, we used only the middle ‘setting’ label, because we think this adequately separates the environments in the movie such that they are not too broad, such as ‘Greenbow Alabama’, but also not so specific that it did not give enough reoccurring locations throughout the movie. This label described environments like ‘Gump House’ or ‘football stadium’.

2.1.4. PPA masks

Sengupta et al. (2016) created individual PPA masks for every subject from the StudyForrest dataset using a functional localizer. Their approach subjected their participants to several types of images, e.g. faces, houses, outdoor scenes, and scrambled images. The fMRI data for these image categories were contrasted, and the voxels that were specifically sensitive to houses and scenes were selected as the PPA mask for the subject. In most subjects, this resulted in a left and right PPA cluster, except for two subjects where only a right cluster was found. Due to the methods in our research, we need to compare activity in the same region across all participants, so we combine the individual masks to derive a common PPA mask. The individual masks were aligned to normal space such that they can be used together for further processing.

2.2. Analysis

Our goal was to relate our ISC scores in the PPA with location scores and movie progression. For this, we had to extract the fMRI data in the PPA from the whole-brain data, perform correlation analysis, and link the results with the location segments. Then, we performed regression analysis on the whole-movie ISC time course, as well as the location ISC scores with location occurrence (LO) count as the predictor variable.

2.2.1. Location segments

The original location annotations contained separate labels for every shot, but these shots may have been in the same location. This is why we combined consecutive labels with identical settings such that scene switches were ignored (Figure 1).

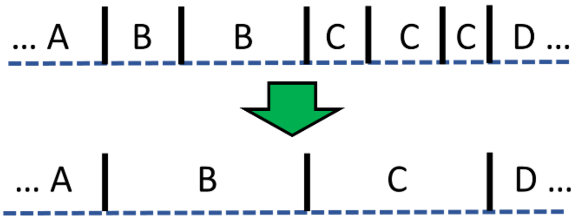


Figure 1: Visualization of the way location segments are merged.

An LO count value was assigned to every location segment and was defined as the number of times the location has shown up in the movie until and including the current segment. The segment for the first occurrence of each location, therefore, gets a value of 1.

2.2.2. Common PPA mask

To compute correlation scores between subjects in our region of interest, we needed a common set of voxels representing the PPA in all participants as well as possible. To achieve this, we combined all individual PPA masks, including both left and right clusters. Afterward, we extracted a set of voxels using an overlap threshold such that there are enough voxels available. The overlap also needed to be high enough such that the voxels representing the PPA are not too specific for a minority of participants. We aimed to create a mask of at least 100 voxels, and therefore we decided on an overlap threshold of 5 subjects, as this resulted in 101 voxels. Figure 3 shows how many voxels were available for other thresholds. The resulting common PPA mask was located medially in the inferior temporo-occipital cortex (Figure 2).

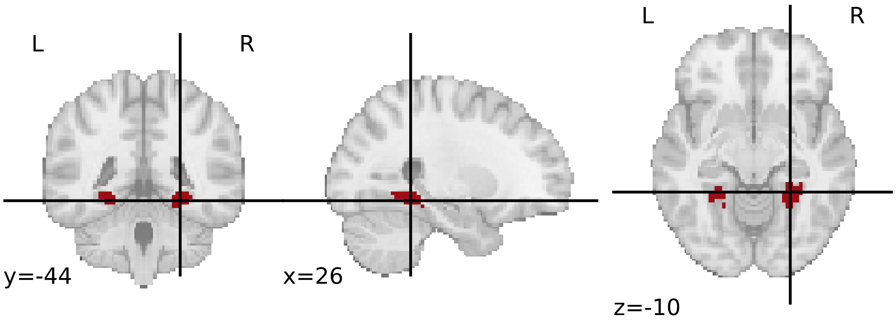


Figure 2: The two clusters of the common PPA mask are shown in red.

Threshold	Voxels
1	438
2	290
3	201
4	141
5	101
6	79
7	61
8	39

Table 1: Other subject thresholds for the common PPA mask resulted in different numbers of voxels.

2.2.3. Mapping fMRI images to locations

Lining up the fMRI images to the location timestamps required us to map the TRs to time in seconds, as well as correct for the hemodynamic response function delay of 5 seconds to match the TRs to the movie timeline. Retrieving the corresponding fMRI volumes for each location segment was done as follows: first, we add the delay of 5 seconds to the location onset, then we determined the starting TR as the first one that fully overlaps with the location segment. The last TR was determined by taking the last one that overlaps for any duration with the current location. The first and last TR plus all the TRs in between were assigned to the location segment.

2.2.4. Inter-subject correlation

As opposed to the research from Geerligs et al. (2016), we will take a purely spatial approach and look at multi-voxel activity patterns, while ignoring the synchronization of temporal activity patterns. Our method of measuring synchronization uses the Pearson correlation coefficient, which is widely used and performs better than alternative methods (Bobadilla-Suarez et al. 2020). For every participant, we computed an ISC time course for the whole movie, with the eight runs concatenated. For every time step, Pearson's correlation coefficient was calculated between the fMRI volume of the participant and the averaged volume for all other participants. The resulting 15 ISC time courses were also averaged across participants to create one ISC time course for the sole purpose of visualization. We found that run 4 contained significantly higher ISC values than the other runs, which can be explained by the fact that hyperalignment was computed using the data from this run, and applied to all runs. To prevent distortion of our results, run 4 was not used in any further analysis.

2.2.5. ISC trendlines

To find out whether our ISC time courses contain a significant progression throughout the movie, as was the case in other brain regions (Geerligs and Campbell 2018), we applied linear regression using the least-squares estimation method, with time as the predictor variable. In the previously cited study, the ISC increase was seen on an 8-minute timescale, and it could be the case that the ISC reaches a ceiling shortly after this duration. We therefore also fitted trendlines for each separate run to find out if there was a greater effect on these shorter timescales. If the whole-movie trendline is significant, we will correct for this overall ISC increase to ensure that the location results are not due to the effect of watch time. Using the per-run trendlines for correction is not appropriate as that would result in sudden changes in ISC between the runs, because the trendlines do not necessarily align with each other.

After we got the whole-movie and per-run trendlines for each subject, we used one-sample t-tests on the results from each of the runs and the whole movie to find out whether these trends can be generalized to the larger population.

2.2.6. ISC difference per location segment

For every subject, we perform the following analysis: For every location segment that meets the minimum duration length, we calculate the ISC difference from baseline, where the baseline is defined by the ISC values before and after the segment. We use a duration threshold of 10 TRs, such that the segment provides an adequate number of fMRI measurements to represent the activity for this location, and that there are also enough segments available of at least 10 TRs. If a segment meets the threshold, we take the average ISC value of the middle 10 TRs of this segment. Next, the 10 ISC values preceding and succeeding the segment (5 on each side) were averaged, acting as the baseline. If the segment was at the beginning or end of a run, more of either the preceding or succeeding values were used to keep the number of samples to 10. This average was then subtracted from the average ISC value of the segment, giving the ISC difference from baseline.

As most locations do not appear more than twice with a duration longer than the threshold, we omitted the results from these segments. Four location labels appeared more than twice with a sufficient duration, shown in Table 2.

Location label	**Available segments**
‘Gump House’	9
‘access-road’	5
‘bench at bus stop’	4
‘on the boat’	4
other labels	2 or less

Table 2: Available segments for location labels that fit the TR threshold.

2.2.7. Regression analysis on LO count and ISC

For every subject, a linear least-squares regression analysis was performed on the ISC differences of the location segments with LO count as the predictor variable. The resulting slopes of the linear fits for every subject were then combined using a one-sample t-test, which tests whether the sample mean is higher than the expected value in our null hypothesis (slope ≤ 0).

3. Results

3.1. Inter-subject correlation

Figure 3 shows the across-subject average ISC time course for every fMRI measurement over time, where the data for all runs are concatenated, along with run and location onsets. In run 4, the effect of hyperalignment can be seen, which gives this run much higher correlation scores. The individual ISC time courses are shown in Figure A2.

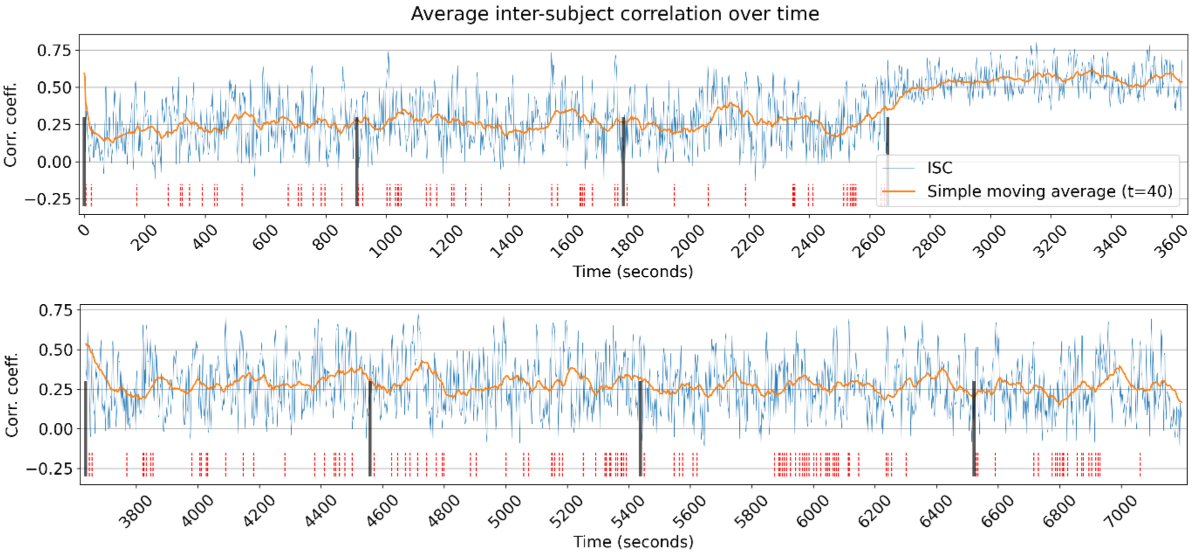


Figure 3: The vertical black bars indicate the onsets of each run, while the red markers indicate the onsets of locations. To give a better idea of the progression of ISC, a simple moving average with a window of 40 seconds is added to the graph.

3.2. Whole-movie trendline

Table 3 shows the resulting linear fits for every subject's ISC time course, with time as the predictor variable.

The mean slope of our subjects' slopes was 7.642×10^{6}. A one-tailed one-sample t-test was applied to the slopes (DF = 14, t = 3.244, α = 0.025), resulting in insufficient confidence (p = 0.0029) in our hypothesis, meaning there is no significant increase in synchronization over the whole movie.

Subject	Fit (ISC =)
1	8.884×10^{-7} t + 0.217
2	7.827×10^{-6} t + 0.243
3	3.500×10^{-6} t + 0.254
4	3.611×10^{-6} t + 0.263
5	7.801×10^{-6} t + 0.213
6	5.605×10^{-6} t + 0.235
9	1.411×10^{-6} t + 0.188
10	2.483×10^{-5} t + 0.278
14	-1.579×10^{-6} t + 0.308
15	9.785×10^{-6} t + 0.292
16	8.246×10^{-6} t + 0.287
17	-7.182×10^{-6} t + 0.314
18	1.016×10^{-5} t + 0.291
19	2.802×10^{-5} t + 0.248
20	1.171×10^{-5} t + 0.169

Table 3: Linear fits for whole-movie ISC time courses per subject, with *t* as time in seconds.

3.3. Per-run trendlines

The per-run slopes for every subject are shown in Table A2. We omitted the intersects, as they are not important for this study. For every run, we applied a one-tailed one-sample t-test. The results of these tests are shown in Table 2.

Run	Sample mean	Sample SD	t-value	p-value
1	2.119×10^{-4}	8.430×10^{-5}	9.40	< 0.001
2	-1.392×10^{-6}	9.430×10^{-5}	-0.0553	0.52
3	1.042×10^{-4}	1.550×10^{-4}	2.52	0.012
5	1.719×10^{-4}	1.371×10^{-4}	4.69	< 0.001
6	1.059×10^{-5}	7.936×10^{-5}	0.499	0.31
7	2.940×10^{-5}	9.390×10^{-5}	1.17	0.13
8	-1.329×10^{-4}	1.832×10^{-4}	-2.71	0.99

Table 2: Results from one-sample t-tests on the slopes of the linear fits in ISC for every run, showing the mean slope, standard deviation of the slopes, t-value, and p-value.

Synchronization in the PPA appears to increase in runs 1, 3, and 5, but not in the other runs.

3.4. Regression analysis on LO count and ISC

For every subject, the regression analysis on ISC difference and LO count resulted in a positive slope ($N = 15$, Mean = 0.0086, SD = 0.0046) (see Figure A1). A one-sample t-test on the slopes gave a significant result with very high confidence ($DF = 14$, $t = 7.22$, $p < 0.001$). This means that we can reject the null hypothesis and conclude that, as subjects get more familiar with locations through repeated exposure, the synchronization in the PPA increases between subjects during these segments.

4. Discussion

We found that synchronization of activity in the PPA during movie watching is affected by watch time at the beginning of the sessions, but does not further increase to the same degree in later consecutive runs, nor does it significantly increase over the whole movie. We also found that synchronization in the PPA is positively affected by repeated exposure to locations in the movie.

Our results suggest that familiarity with locations through repeated exposure increases the degree to which the internal representations of these places are synchronized between subjects. Watch time, irrespective of location motifs, seems to also have a positive effect at the beginning of watching sessions, but this seems to reach a ceiling after some time has passed. Just like the overall increase in synchronization found by Geerligs et al. (2018) in the frontoparietal control network, the medial temporal lobes, and the medial prefrontal cortex, we found an increase in synchronization in the PPA at similar time scales during the beginning of watching sessions. After these initial increases, we found no substantial further increases of the same magnitude. These initial increases could be a result of the subjects mentally adjusting to the movie. Before the start of run 5, subjects had a pause of approximately 10 minutes outside the scanner, which may have disrupted the relatively stable representation of the movie environments, and required some time to re-establish when they continued watching the movie. We cannot provide a possible explanation for the smaller increase in synchronization in run 3.

Epstein et al. (1999) found that PPA activity was unaffected by subjects' familiarity with depicted places, which is in stark contrast to our findings. A possible explanation for this difference in results could be the fact that we used a more naturalistic stimulus with dynamic imagery, as opposed to the static images used in their research.

Further research may find a similar effect on synchronization from shared stimuli on different brain regions involved with different aspects of perception, such as how repeated exposure to specific faces may increase synchrony in the fusiform face area. Another question that could be studied is whether recall performance of movies or other naturalistic stimuli is related to synchronization between subjects. We speculate that subjects with better recall also score higher on synchronization during stimuli exposure because they might have paid better attention and built up a stronger and more complete model of the stimuli.

In our study, we combined the left and right PPA clusters' activity, but analyzing these two clusters separately could provide more insights into their functional separation. If the analysis shows that one side consistently has lower ISC scores, it could indicate a general tendency of this side of the brain surrounding the PPA to be more idiosyncratic in the way it processes information.

4.1 Limitations

4.1.1. Idiosyncrasies in cortical organization

Humans have a very similar functional organization of brain function at coarse scales, but increasingly differ in cortical functional architecture when looking at smaller scales. Feilong et al. (2018) looked into these differences and found that individuals reliably differ in fine-scaled functional architecture even after hyperalignment. Since our research directly compares hyperaligned fMRI data, these idiosyncrasies are not accounted for, resulting in lower synchronization scores than would otherwise be obtained if these small-scale differences were better functionally aligned.

The fact that the functional localizer from Sengupta et al. (2016) created different PPA masks for each subject also shows that individuals possess unique functional organizations in regions for processing places and scenes.

4.1.2 Spatial versus temporal ISC

Our method of calculating synchronization uses purely spatial activity patterns. Taking into account temporal patterns in activity may lead to different results. Kauppi et al. (2010) studied frequency-band-specific ISC during movie watching and found that regions in the frontal and temporal lobes showed ISC mostly in low-frequency bands, while visual cortical areas show ISC at higher frequencies. They discuss, based on other research, that this difference could be explained by the hierarchy of temporal receptive windows, where higher-order cortical areas process stimuli over longer timescales. Diving into frequency bands to measure temporal ISC could reveal specific frequencies that show higher degrees of synchronization between subjects than a purely spatial method, and might also give rise to different conclusions.

Nastase et al. (2019) looked at both spatial and temporal ISC analysis methods. They discussed that these methods can reveal different sources of shared responses across subjects. Because our approach ignored temporal activity patterns in the comparisons between subjects, there

5. Conclusions

Our study found that repeated occurrence of locations in a movie has a positive effect on synchrony in the brain area responsible for processing places, however, synchronization during the whole movie was not affected by long-term watch time, and remained relatively consistent after initial increases. Our takeaway from these results is that people build up more shared internal representations as they get more familiar with novel environments.

References

- Geerligs, L., & Campbell, K. L. (2018). Age-related differences in information processing during movie watching. Neurobiology of Aging, 72, 106-120.
- Willems, R. M., Nastase, S. A., & Milivojevic, B. (2020). Narratives for neuroscience. Trends in neurosciences, 43(5), 271-273.
- Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., & Malach, R. (2004). Intersubject synchronization of cortical activity during natural vision. science, 303(5664), 1634-1640.
- Oetringer, D.A., Gözükara, D., Güçlü, U., Geerligs, L. (2022). Changes in the external environment are reflected in stable patterns of brain activity that underlie event segmentation. [Manuscript in preparation]
- Baldassano, C., Chen, J., Zadbood, A., Pillow, J. W., Hasson, U., & Norman, K. A. (2017). Discovering event structure in continuous narrative perception and memory. *Neuron*, *95*(3), 709-721.
- Epstein, R., & Kanwisher, N. (1998). A cortical representation of the local visual environment. Nature, 392(6676), 598-601.
- Epstein, R. A. (2008). Parahippocampal and retrosplenial contributions to human spatial navigation. Trends in cognitive sciences, 12(10), 388-396.
- Liu, X., Zhen, Z., Yang, A., Bai, H., & Liu, J. (2019). A manually denoised audio-visual movie watching fMRI dataset for the studyforrest project. Scientific data, 6(1), 1-9.
- Hanke, M., Adelhöfer, N., Kottke, D. et al. A studyforrest extension, simultaneous fMRI and eye gaze recordings during prolonged natural stimulation. Sci Data 3, 160092 (2016). https://doi.org/10.1038/sdata.2016.92
- Hanke, M., Baumgartner, F. J., Ibe, P., Kaule, F. R., Pollmann, S., Speck, O., ... & Stadler, J. (2014). A high-resolution 7-Tesla fMRI dataset from complex natural stimulation with an audio movie. Scientific data, 1(1), 1-18.
- Haxby, J. V., Guntupalli, J. S., Nastase, S. A., & Feilong, M. (2020). Hyperalignment: Modeling shared information encoded in idiosyncratic cortical topographies. Elife, 9, e56601.
- Häusler, C. O., & Hanke, M. (2016). An annotation of cuts, depicted locations, and temporal progression in the motion picture" Forrest Gump". F1000Research, 5.
- Sengupta, A., Kaule, F., Guntupalli, J. et al. A studyforrest extension, retinotopic mapping and localization of higher visual areas. Sci Data 3, 160093 (2016). https://doi.org/10.1038/sdata.2016.93
- Bobadilla-Suarez, S., Ahlheim, C., Mehrotra, A., Panos, A., & Love, B. C. (2020). Measures of neural similarity. Computational brain & behavior, 3(4), 369-383.
- Epstein, R., Harris, A., Stanley, D., & Kanwisher, N. (1999). The parahippocampal place area: recognition, navigation, or encoding?. Neuron, 23(1), 115-125.
- Feilong, M., Nastase, S. A., Guntupalli, J. S., & Haxby, J. V. (2018). Reliable individual differences in fine-grained cortical functional architecture. NeuroImage, 183, 375-386.
- Kauppi, J. P., Jääskeläinen, I. P., Sams, M., & Tohka, J. (2010). Inter-subject correlation of brain hemodynamic responses during watching a movie: localization in space and frequency. *Frontiers in* neuroinformatics, 4, 5.
- Nastase, S. A., Gazzola, V., Hasson, U., & Keysers, C. (2019). Measuring shared responses across subjects using intersubject correlation. Social Cognitive and Affective Neuroscience, 14(6), 667-685.

Appendix

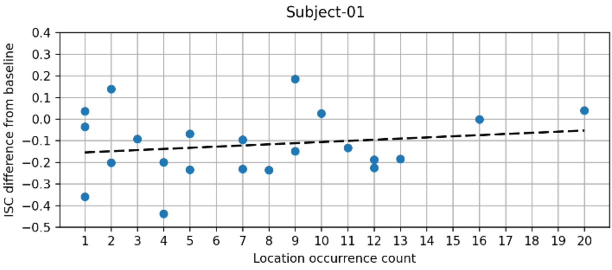
Subject	**Run 1**	**Run 2**	**Run 3**	**Run 5**	**Run 6**	**Run 7**	**Run 8**
1	2.75×10^{-4}	-6.66×10^{-5}	6.87×10^{-5}	3.87×10^{-5}	6.18×10^{-5}	6.70×10^{-5}	-5.04×10^{-4}
2	2.63×10^{-4}	-2.19×10^{-5}	2.29×10^{-4}	1.53×10^{-4}	6.33×10^{-5}	-5.01×10^{-5}	-1.13×10^{-5}
3	1.12×10^{-4}	1.82×10^{-4}	1.11×10^{-5}	1.55×10^{-4}	1.22×10^{-4}	1.87×10^{-4}	-2.79×10^{-5}
4	2.40×10^{-4}	-5.19×10^{-5}	1.86×10^{-5}	2.01×10^{-4}	-9.76×10^{-5}	1.09×10^{-4}	-1.075×10^{-4}
5	2.30×10^{-4}	-3.85×10^{-5}	-2.29×10^{-5}	1.48×10^{-4}	3.88×10^{-5}	2.07×10^{-4}	1.41×10^{-4}
6	2.83×10^{-4}	-7.27×10^{-5}	6.31×10^{-5}	2.59×10^{-4}	3.35×10^{-5}	6.92×10^{-5}	8.35×10^{-5}
7	1.34×10^{-4}	-8.52×10^{-5}	6.88×10^{-5}	3.21×10^{-4}	2.61×10^{-5}	1.48×10^{-5}	6.46×10^{-5}
8	1.99×10^{-4}	1.14×10^{-4}	1.16×10^{-4}	1.96×10^{-4}	1.01×10^{-4}	-3.42×10^{-5}	-1.08×10^{-4}
9	1.72×10^{-4}	1.49×10^{-4}	1.10×10^{-4}	4.17×10^{-4}	-8.63×10^{-5}	-1.20×10^{-4}	-3.36×10^{-4}
10	5.53×10^{-5}	9.25×10^{-5}	3.04×10^{-4}	1.87×10^{-4}	-1.31×10^{-4}	-1.76×10^{-5}	-2.816×10^{-4}
11	1.98×10^{-4}	-5.44×10^{-5}	-3.33×10^{-4}	2.32×10^{-4}	-7.47×10^{-5}	-4.98×10^{-6}	9.64×10^{-5}
12	2.71×10^{-4}	-1.45×10^{-4}	3.09×10^{-4}	1.63×10^{-4}	-3.20×10^{-5}	-1.10×10^{-4}	-2.44×10^{-4}
13	4.17×10^{-4}	-1.94×10^{-5}	1.83×10^{-4}	1.10×10^{-4}	1.39×10^{-4}	-4.18×10^{-5}	-2.78×10^{-4}
14	1.39×10^{-4}	-7.44×10^{-5}	2.57×10^{-4}	2.28×10^{-4}	-2.82×10^{-6}	8.87×10^{-5}	-2.90×10^{-4}
15	1.90×10^{-4}	7.15×10^{-5}	1.80×10^{-4}	-2.29×10^{-4}	-2.28×10^{-6}	7.64×10^{-5}	-1.90×10^{-4}

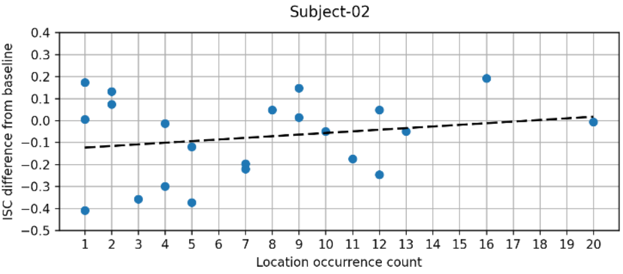
Table A1: Per-subject slopes of linear fits in ISC time courses for every run.

ΔISC – LO count regression results

Subject	Fit (ΔISC =)
01	0.00533 × LO – 0.160
02	0.00740 × LO – 0.131
03	0.01575 × LO – 0.161
04	0.00554 × LO – 0.040
05	0.00712 × LO – 0.128
06	0.00132 × LO – 0.050
09	0.00800 × LO – 0.101
10	0.00705 × LO – 0.132
14	0.00259 × LO – 0.048
15	0.01444 × LO – 0.193
16	0.00678 × LO – 0.100
17	0.01751 × LO – 0.244
18	0.01225 × LO – 0.184
19	0.00821 × LO – 0.120
20	0.00994 × LO – 0.166

Table A2: Linear fits for ΔISC per subject, with location occurrence (LO) count as the predictor variable.


Subject-01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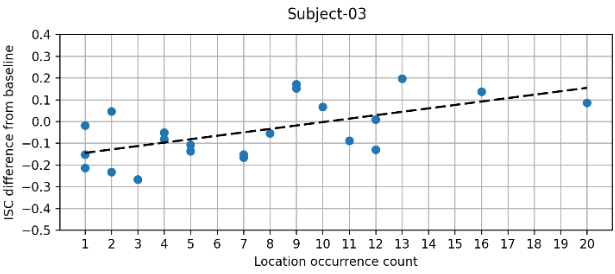
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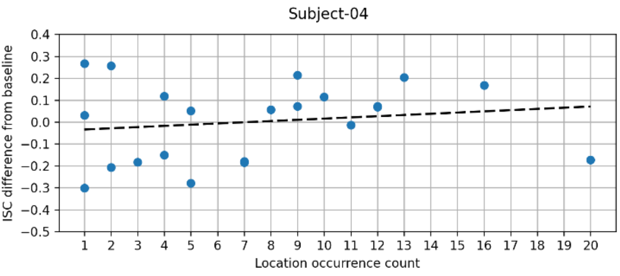
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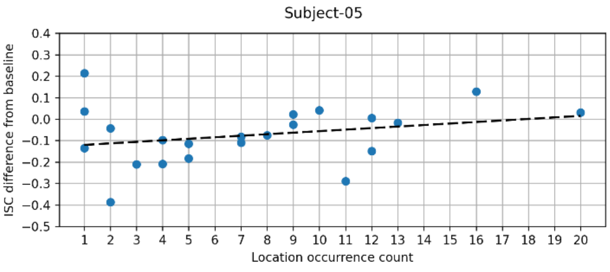
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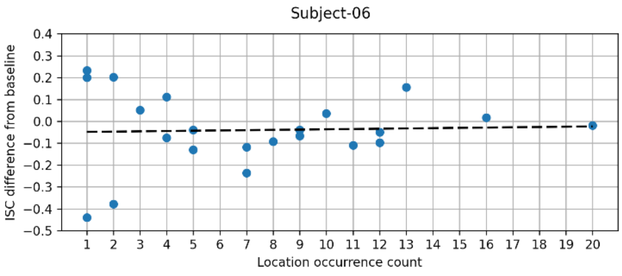
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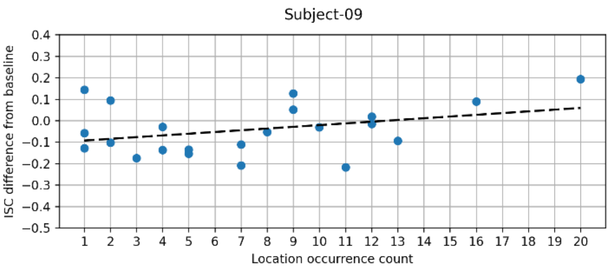
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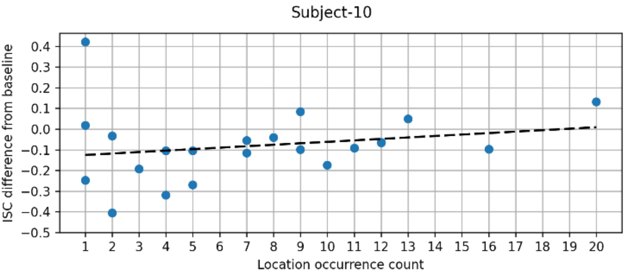
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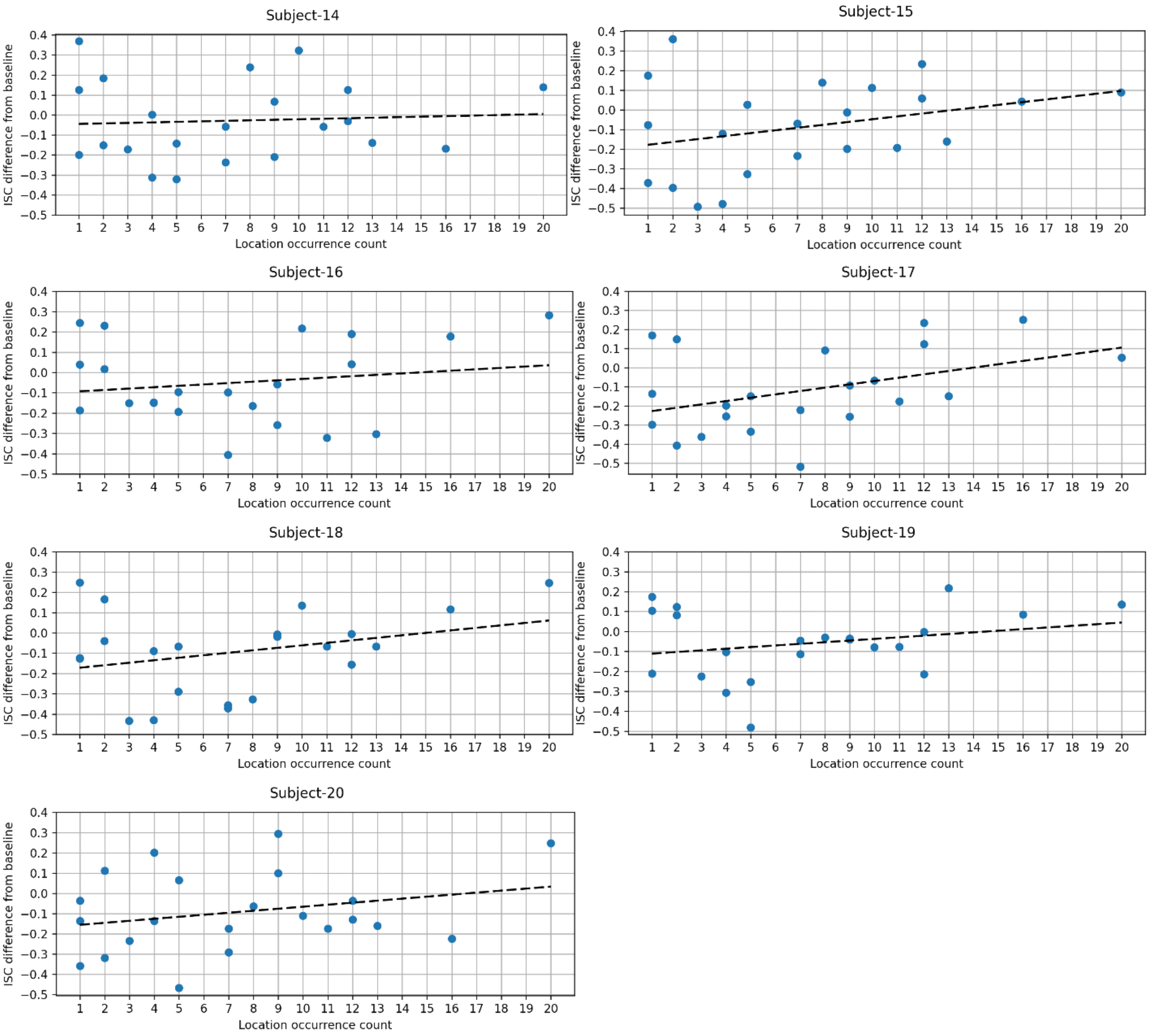
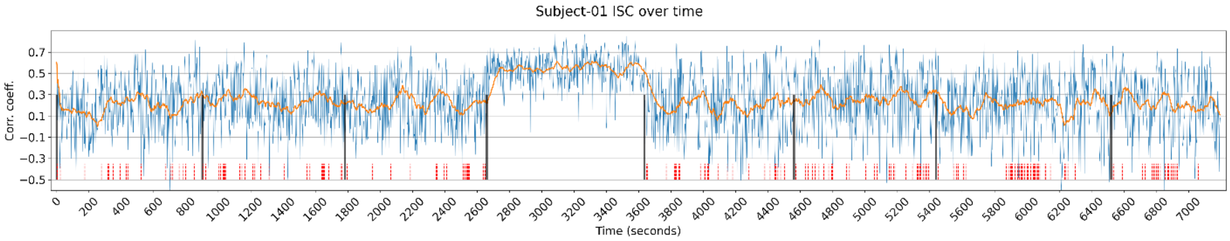
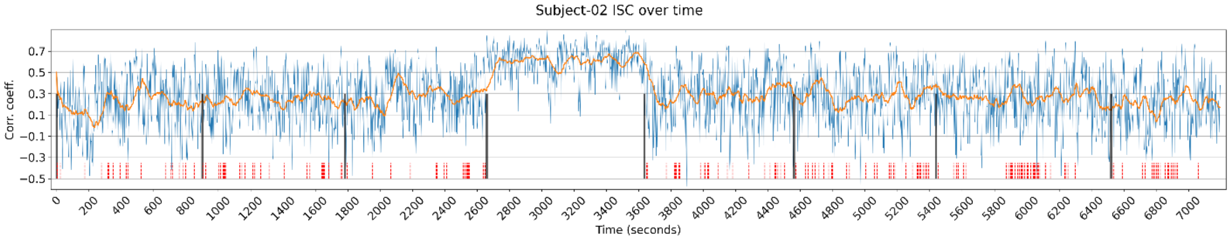
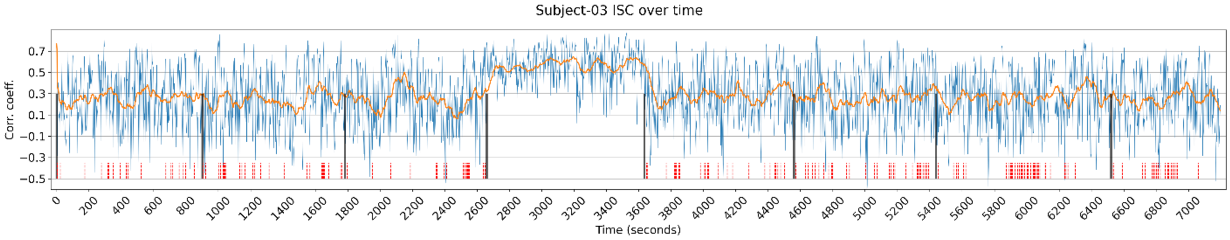


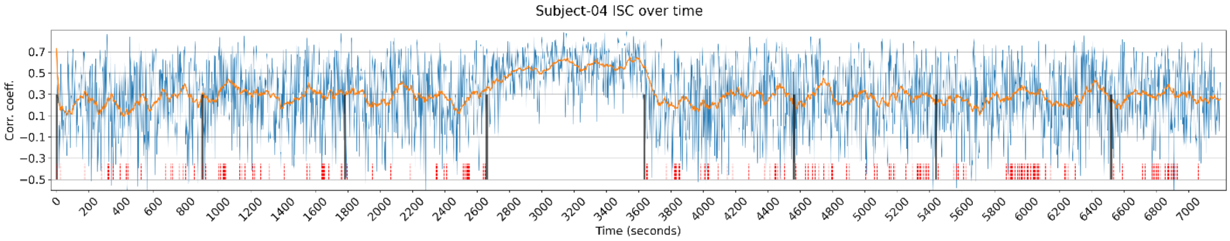
Figure A1: Plots of linear fits for location occurrence count and ISC per subject. Blue dots represent ΔISC values of location segments.

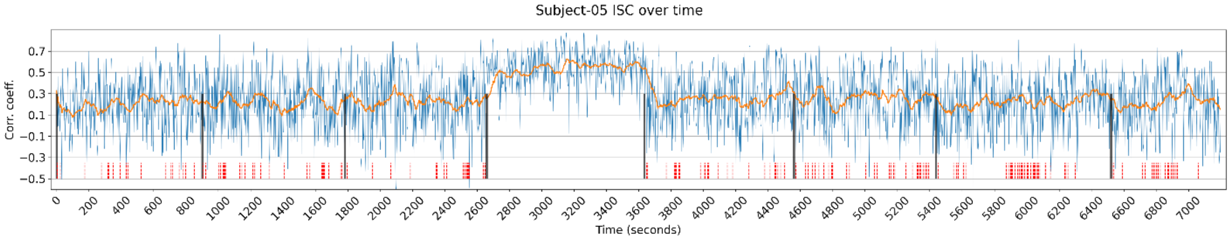
Per-subject ISC time courses

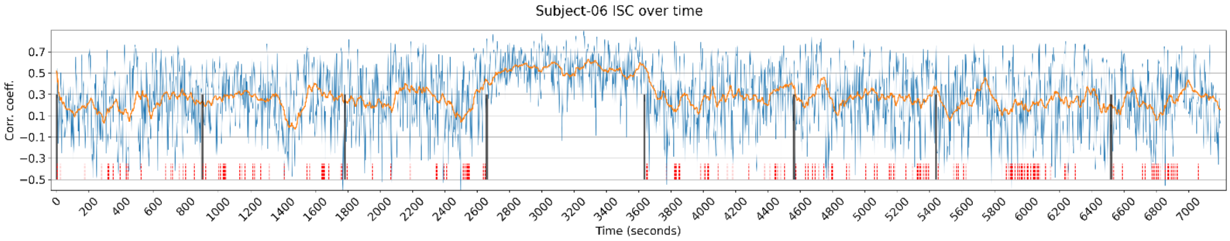

Subject-01 ISC over time

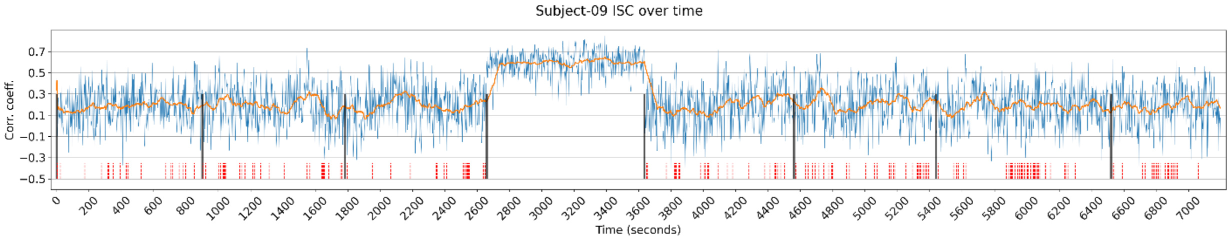

Subject-02 ISC over time


Subject-03 ISC over time


Subject-04 ISC over time


Subject-05 ISC over time


Subject-06 ISC over time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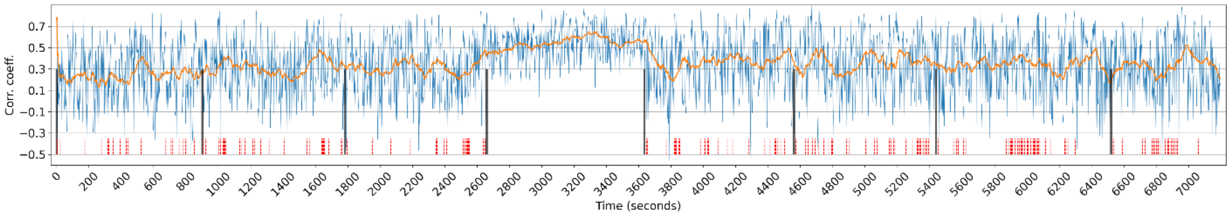
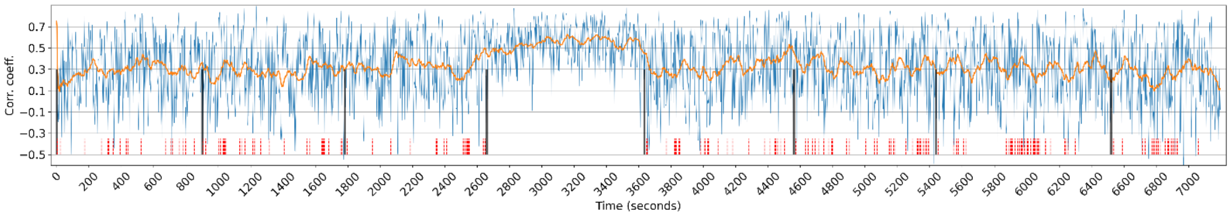
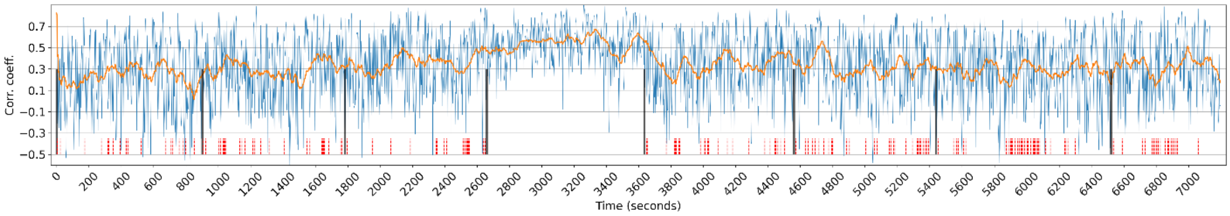
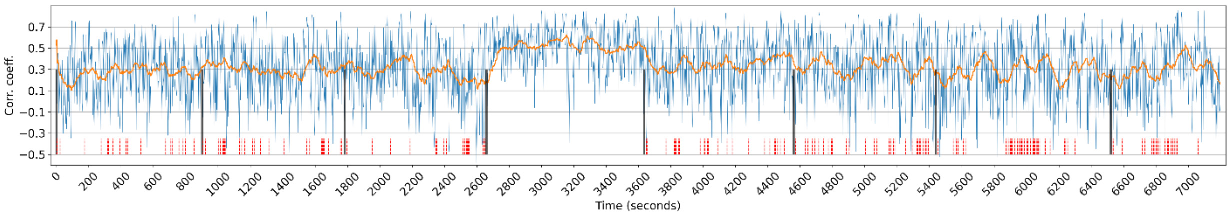
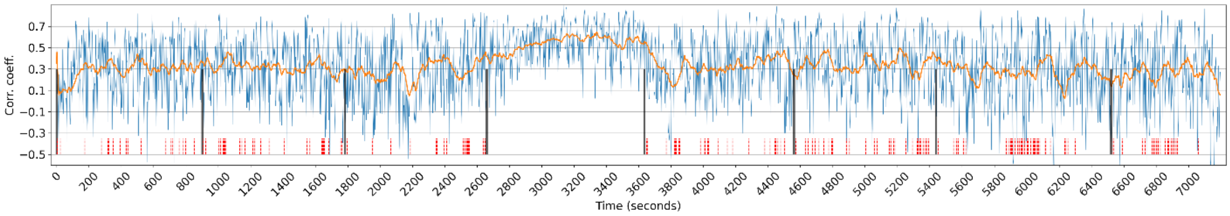
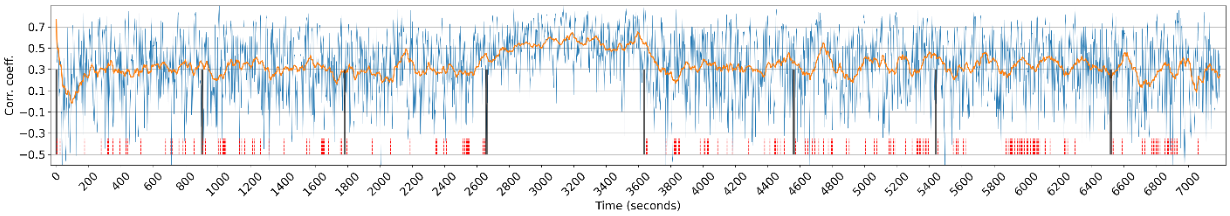

Subject-10 ISC over time


Subject-14 ISC over time


Subject-15 ISC over time


Subject-16 ISC over time


Subject-17 ISC over time


Subject-18 ISC over time

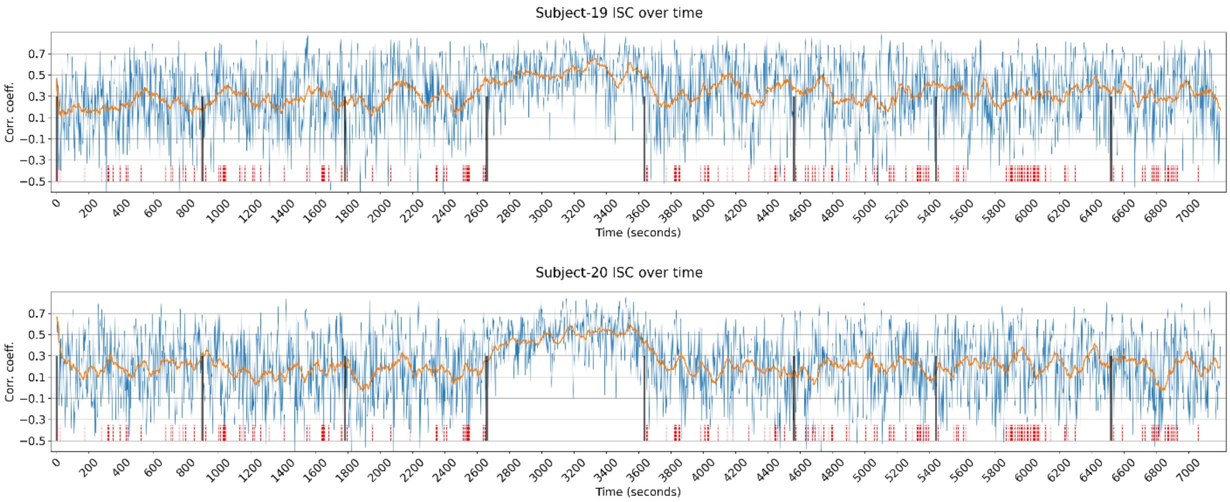


Figure A2: ISC time courses for every subject. The blue line represents the ISC values at every TR, while the orange line shows a simple moving average with a time window of 40 TRs. The vertical black bars indicate the onsets of each run, while the red markers indicate the onsets of locations.