Cingulo-Opercular Interactions with Auditory Cortex Activity During Speech Recognition in Noise

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Introduction

Speech recognition in noise often engages cingulo-opercular cortex [1,2].

Elevated cingulo-opercular activity is observed during challenging task conditions, response errors, and response uncertainty [3], and predicts an increased likelihood of correct word recognition for subsequent trials [1,2]. Thus, cingulo-opercular activity is hypothesized to signal when performance needs to be optimized.

Frontal activity appears to modulate auditory cortex responses to speech [4] and auditory cortex activity patterns specifically reflect dimensions of speech that are critical for task performance [5]. We predicted that cingulo-opercular cortex interacts with auditory cortex to optimize speech recognition in noise.

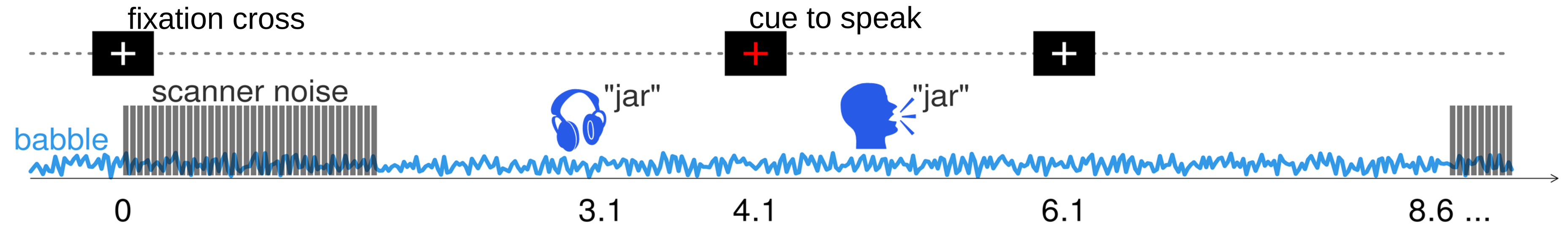
Do auditory cortex and cingulo-opercular cortex encode information about activation in each other and does that interaction relate to word recognition?

Method

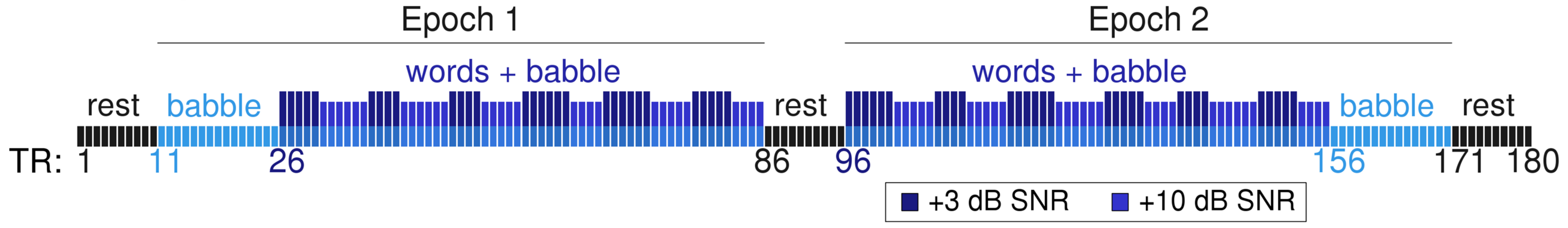
Participants: Younger adults (N = 18, 10 female; 20-38 years of age; mean pure tone thresholds ≤ 9.2 dB HL, 0.25 to 8 kHz; previously analyzed [1]) listened to words with continuous, multitalker babble (+3 or +10 dB signal to noise ratio; SNR).

Task: Repeat the word aloud or say "nope" if it was not recognized.

Trial Design: Sparse fMRI Acquisition (TR = 8.6 sec)



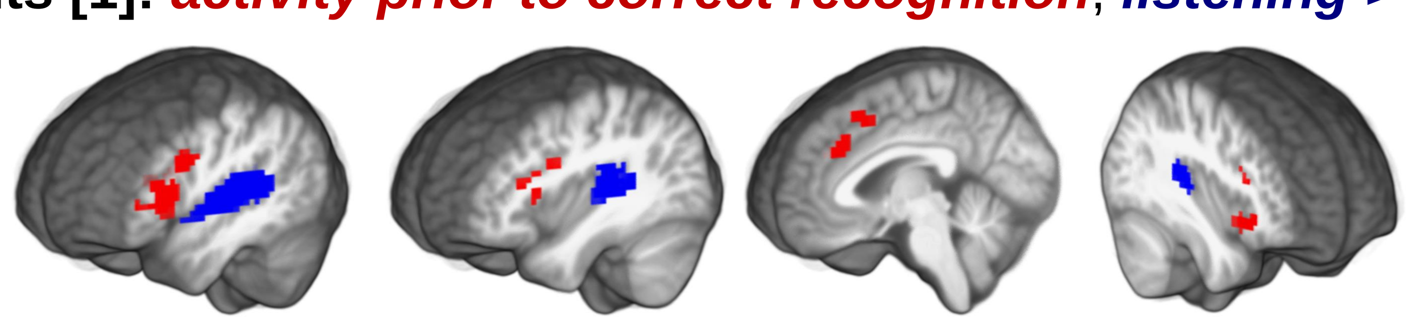
Block Design: Alternating SNR blocks (4-6 trials)



fMRI: 180 T2*-weighted images (3 mm^3 voxels); 25 min 48 sec.

Structural MRI: T1-weighted images (1 mm^3 voxels).

Group results [1]: *activity prior to correct recognition*; *listening > silent rest*.



Statistic map threshold: Z = 3.09, p_{UNC} = 0.001, cluster sizes > 26, p_{FWE} = 0.05.

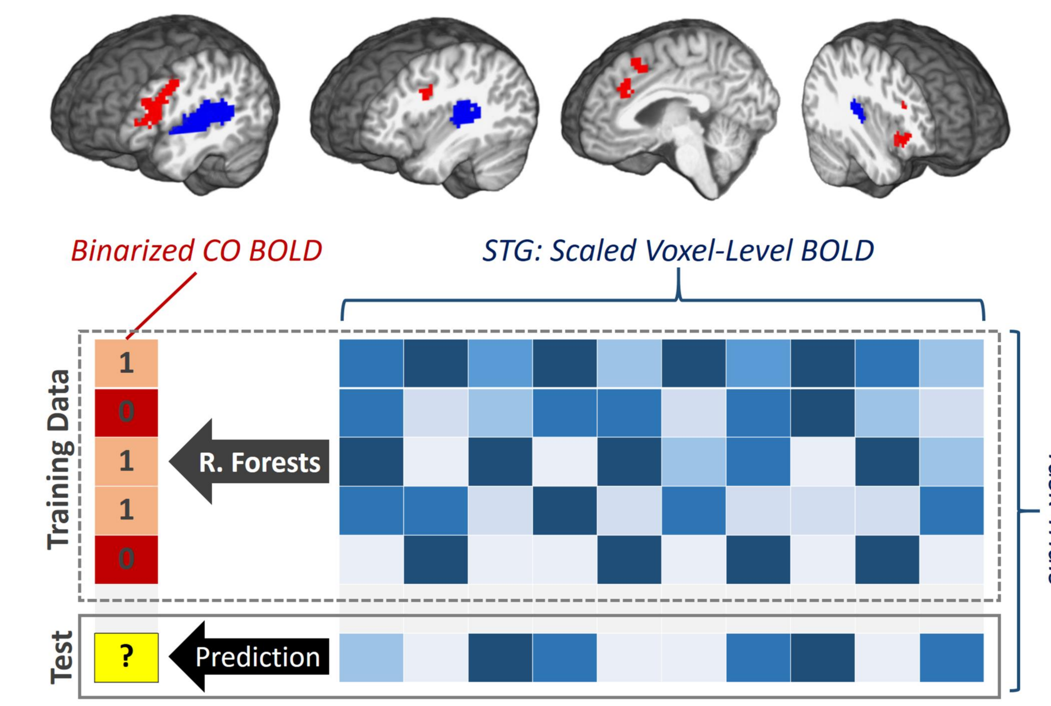
Analysis

Multi-voxel analyses were used to test the prediction that superior temporal gyrus (STG) BOLD patterns encode high or low cingulo-opercular (CO) activity, and vice versa.

Preprocessing. Functional images were aligned, co-registered, smoothed (4mm FWHM), and detrended [6] in native anatomical space. Group statistic maps [1] were spatially transformed [7] to define regions of interest in the native space for each subject.

Classification. The Random Forest (RF) algorithm [8] was trained within-subject to classify trials with higher than average CO activity on the basis of multi-voxel BOLD patterns across STG (i.e. STG→CO). The CO→STG classification was also tested.

Random Forest Classification Procedure



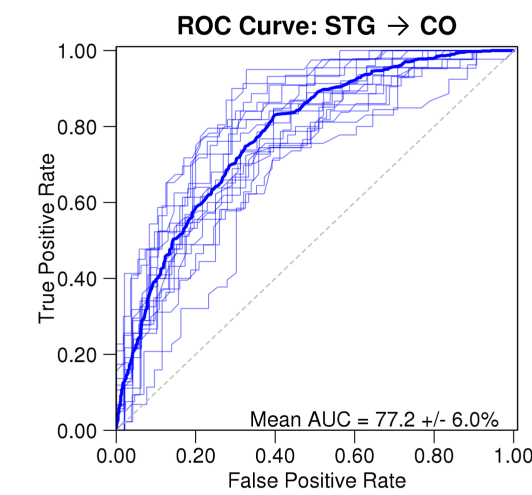
Cross-validation: accuracy was measured by testing each trial independently from the training data.

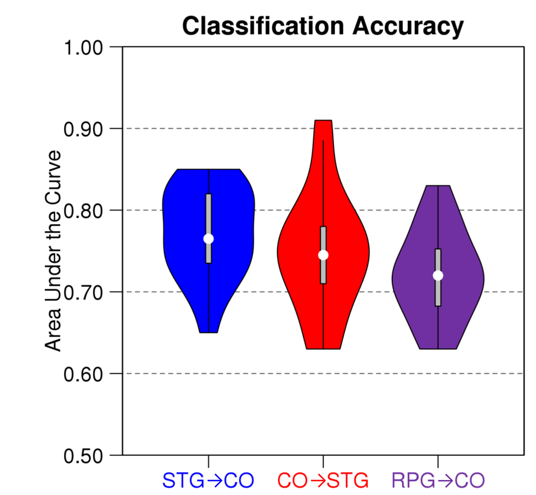
Results

STG→CO STG BOLD patterns classified high or low CO activity (area under the curve, AUC = 77.2 ± 6.0%). Classifications were related to CO activity [Z = 15.79, p < 0.001], after controlling for SNR and performance.

CO→STG CO BOLD patterns classified high or low STG activity [AUC = 74.7 ± 7.0%] and RF accuracy was higher for trials in the +10 than +3 dB SNR condition [Z = 2.46, p = 0.01].

RPG→CO *Control region:* right post-central gyrus (RPG) BOLD patterns classified high or low CO activity [AUC = 72.1 ± 5.0%]; less accurate than STG→CO [t(17) = -3.33, p = 0.002].





RF classification accuracy was higher than chance (50%) for all three analyses [$t(17)$ > 12.96, p < 0.001].

Correlations between predictor voxels and regions: *Z-prime* range = [-0.88, 0.91], *p > 0.18 (post-scaling; all 3 tests)*.

Fewer than 1.6% predictor voxels had significantly increased or decreased BOLD with the target region (p_{BONF} < 0.05).

Conclusions

Diffuse changes in auditory cortex activity patterns were related to cingulo-opercular activity, and cingulo-opercular activity patterns were also related to auditory cortex activity, although neither multivariate association appeared to relate to trial-level word recognition or individual differences in performance.

Multi-voxel classifications provide a potential measure of information transfer between a frontal attention network and auditory cortex, even in the absence of traditional functional connectivity. Questions remain about the specificity of these interactions for optimizing performance and attention.

The current results demonstrate that a complex interaction exists between cingulo-opercular and auditory cortex activity, in the context of a challenging word recognition task.

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