Multi-echo fMRI denoising with physiological and motion information

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INTRODUCTION

Multi-echo denoising removes non-T2* and therefore non-BOLD time series fluctuations. This includes scanner artifacts and head motion. However, breathing related BOLD changes are not removed.

We use the multi-echo ICA denoising[7] method implemented in tedana[4] and additionally removed ICA components that are correlated with head motion, cardiac, and respiratory fluctuations. Our hypothesis was that this additional ICA removal process would help eliminate artifactual BOLD and maintain higher statistical degrees of freedom.

METHODS

Experimental Paradigm

13 participants completed several tasks:

25 min: visual vs audio & word vs nonword task[8]

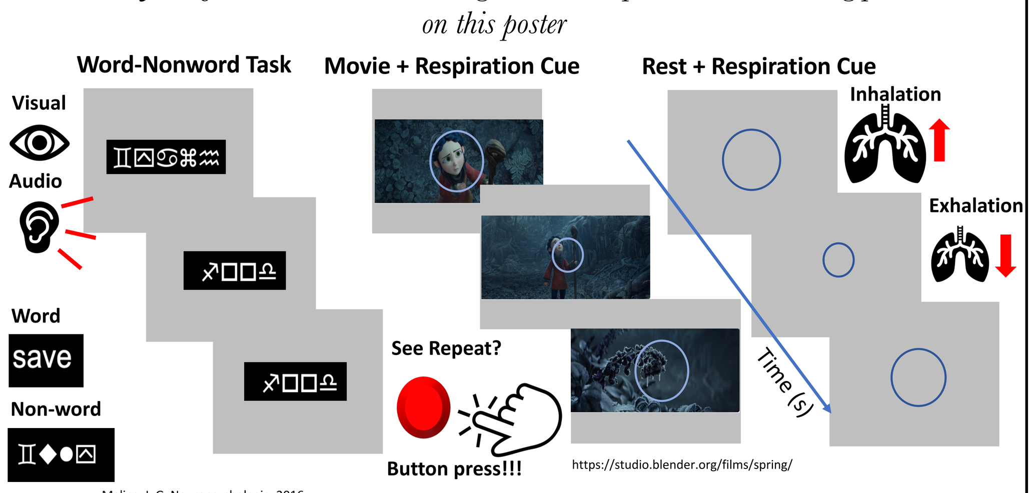
This task should create measurable contrasts between conditions in every brain lobe and in areas with both large and small magnitude responses that can be used to compare methods

8 min: cued breathing task (2X) with the same breathing pattern each run. Breathing rate and depth slowly changes across the run

8 min: movie + cued breathing (2-3X) with different breathing patterns each run

These runs can be used for inter-run and inter-subject correlation (ISC) measurements. Better removal of cardiac and respiratory artifacts should improve ISC between the movie runs and reduce artifactual ISC between the cued breathing runs with common breathing patterns.

Note: Analyses of the movie and breathing runs are in process and not being presented on this poster



Acquisition

3T Siemens Prisma, multi-echo fMRI (CMRR Multi-band EPI, SMS=2 iPAT=2, TE=13.44, 31.7, & 49.96), 3.0 mm isotropic voxels. Stored magnitude & phase information and collected 5 RF-off "noise" volumes at the end of each sequence. Respiratory belt and pulse oximetry recorded.

Data processing

Data were preprocessed with AFNI[3]. Skull stripping and anatomical ROIs were calculated with Freesurfer[5] and functionally localized using the optimally combined data with the Visual-Audio contrast for V1 & A1 and the word-nonword contrast for all other ROIs. Multi-echo ICA denoising used tedana[4]. Cardiac and respiratory frequency variations[6], respiratory volume changes[1], and heart rate changes[2] were calculated using niphlem[10]. Presented GLMs were calculated using 4 conditions: (1) 2nd echo data with motion and 1st derivative of motion traces (Motion), and lateral ventricle ROIs (CSF) as nuisance regressors. (2) The optimal combination of echoes with motion & CSF regressors (3) Optimal combination with tedana rejected ICA components, motion, and CSF as nuisance regressors. (4) Motion, CSF, respiration, & cardiac signals fit to ICA & used as combined nuisance regressors (see Denoising Methods)

Processing code

https://github.com/nimh-sfim/ComplexMultiEcho1

NORDIC

This poster's abstract focused on NORDIC denoising[11] combined with the methods presented here. While still planned, ensuring valid statistics across a combined pipeline required more work.

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REFERENCES

1. Birn, R. M. Neuroimage. 2006, 2. Chang, C, NeuroImage 2009
3. Cox, R. W. Computers and Biomedical Research. 1996
4. DuPre E., Salo, T. Journal of Open Source Software. 2021
5. Fischl, B. Cereb Cortex 200b, 6. Glover, G. Magnetic Resonance Medicine. 2000, 7. Kundu, P. Neuroimage. 2012, 8. Malins, J, Neuropsychologia, 2016, 9. Pruim, R. NeuroImage. 2015, 10. Verstynen, T, Deshpande V., NeuroImage 2011, 11. Vizioli L. Nat Commun 2021

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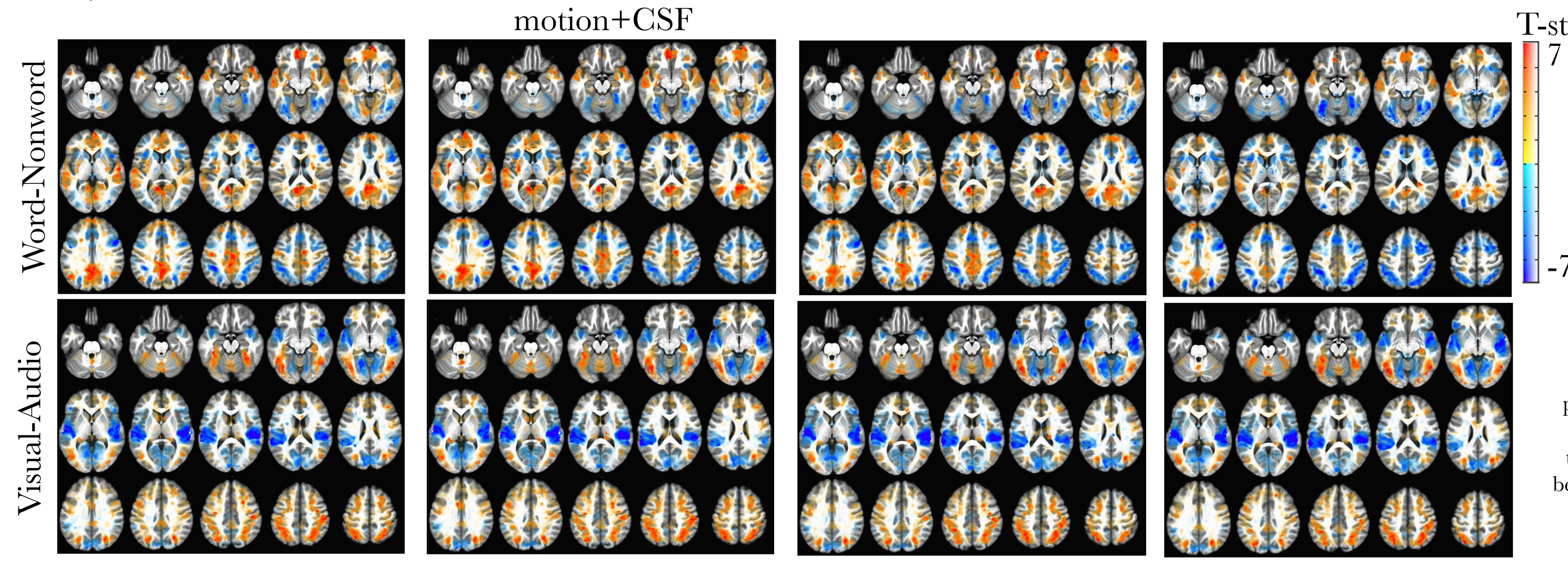
RESULTS

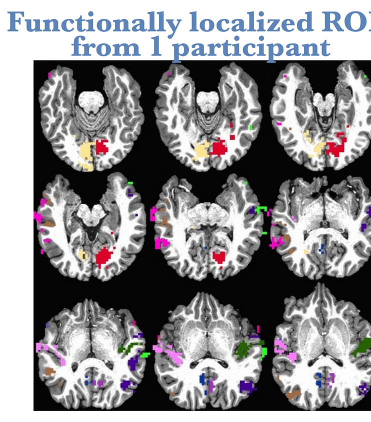
Group maps are similar across processing methods



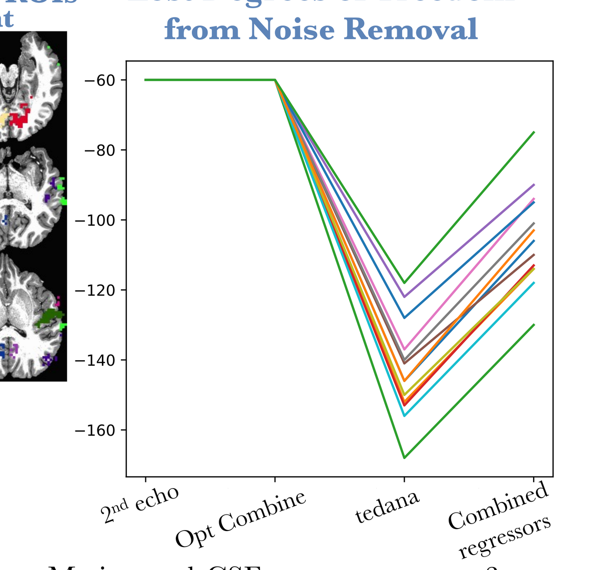
Full color opacity at p<0.001 with increasing transparency below threshold

Optimally combined and tedana show more significant activation than 2nd echo. Combined regressors are similar or slightly less than tedana. Using 3dMVM in AFNI

Functionally localized ROIs from 1 participant

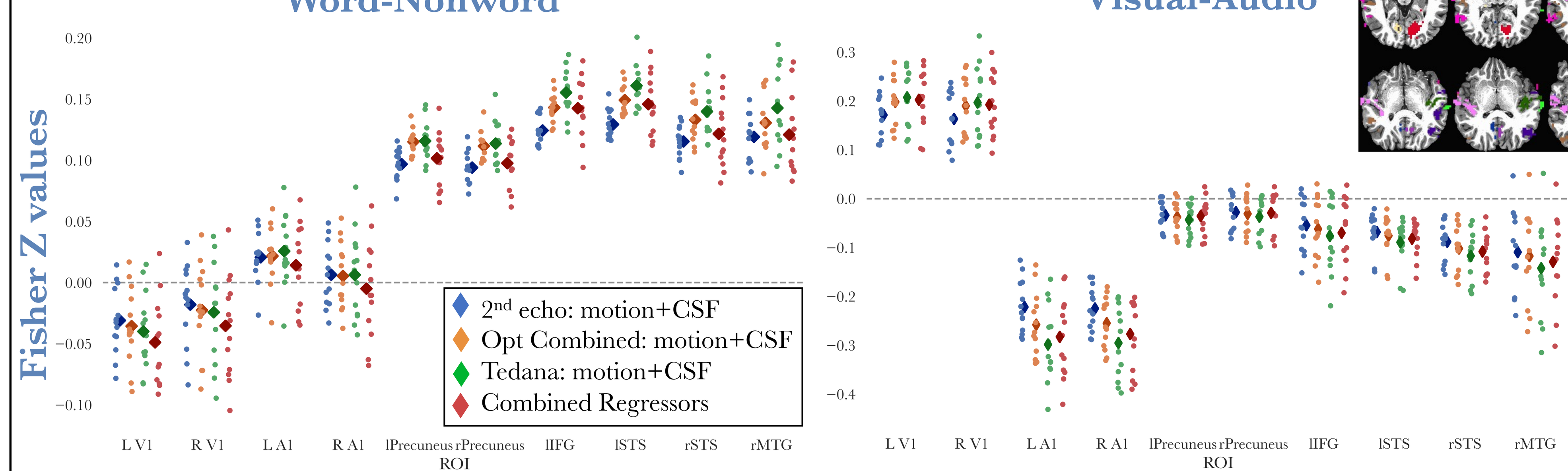


Lost Degrees of Freedom from Noise Removal



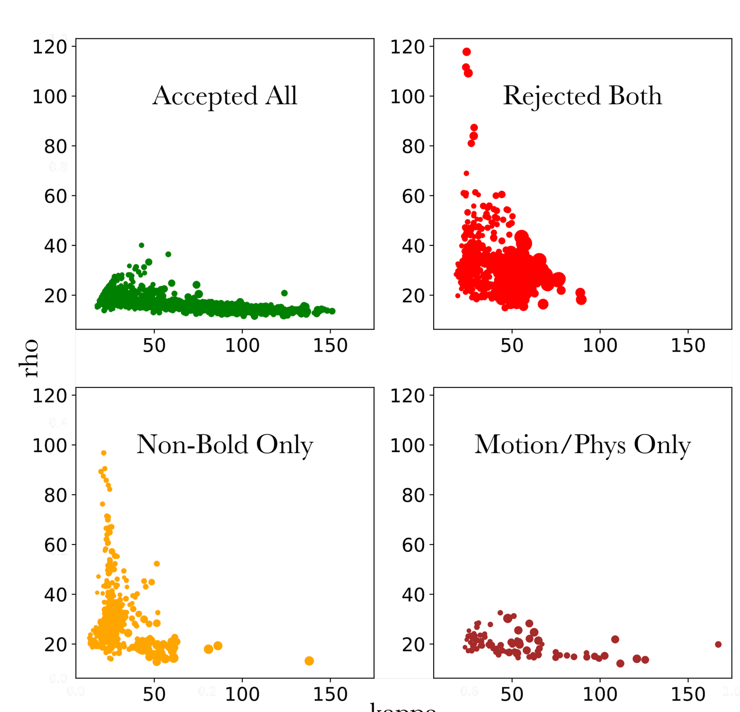
Motion and CSF regressors across 3 runs use 60 DOF for noise removal (of 1035 total for these data). Tedana uses additional DOF that varies by the number of components removed per run, but always includes the 60 DOF lost from motion & CSF. Combined regressors removes overlapping signals between tedana, motion, & CSF and loses fewer DOF even though respiratory and cardiac signals are also modeled. Each line is a subject.

Average Fisher Z values in ROIs for each participant



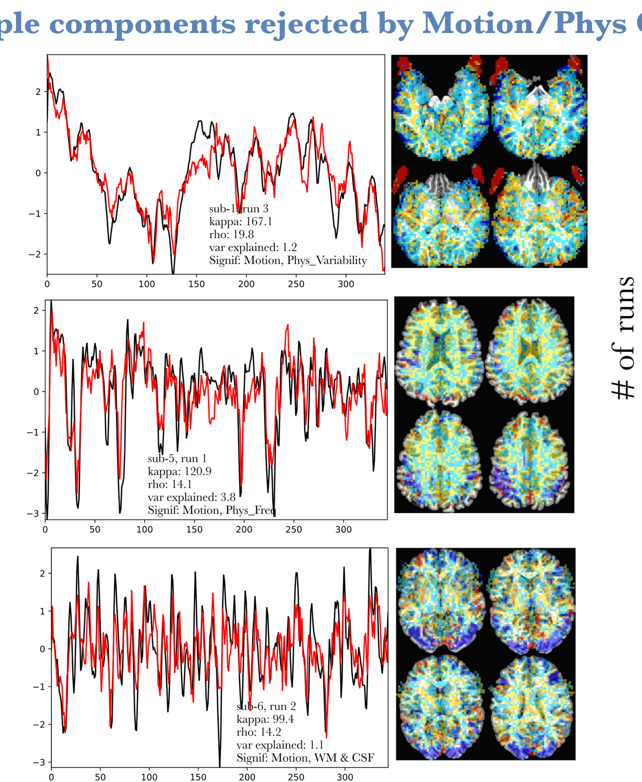
Each dot is a participant (diamonds=mean). For the Word-Nonword contrast, the Fisher Z values increased from echo 2 → optimally combining echoes → tedana denoising. The combined regressors have lower Fisher Z values vs using tedana & motion regressors separately.

Effect of combined regressors on component selection

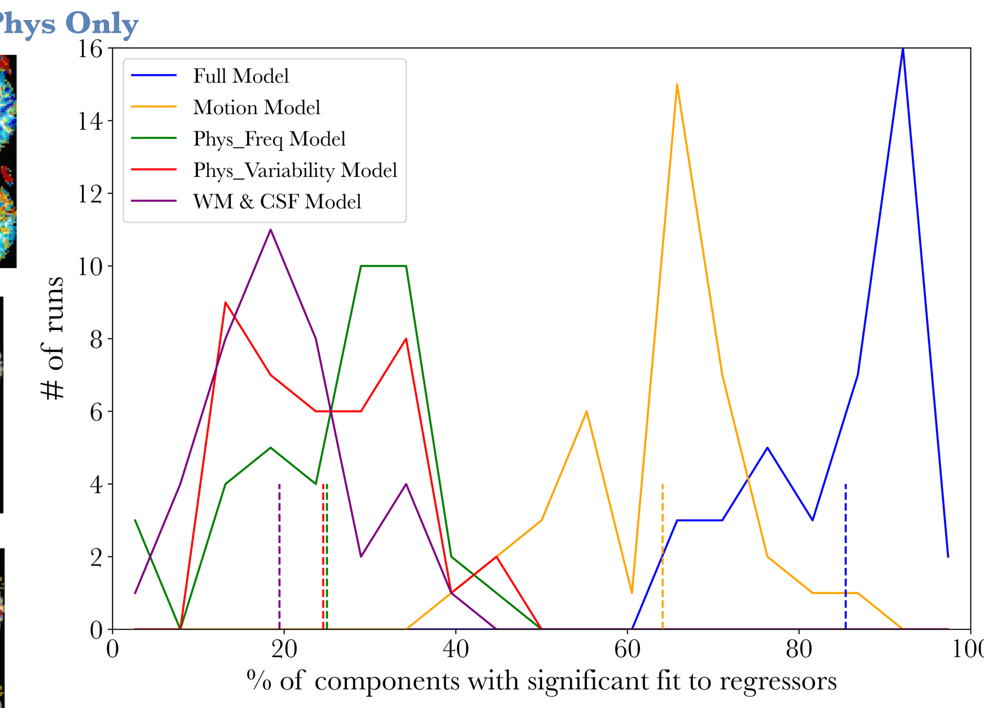


Kappa is a measure of T2* fluctuations and rho is a measure of S0 fluctuations in each component. These plots contain all components from all runs. The components that are rejected due to motion or physiology but were not rejected by tedana tend to have low rho and high kappa.

Example components rejected by Motion/Phys Only



Component time series in black. Model fit in red. Despite high kappa values, there were rejected due to significant model fits nuisance regressors



Many (often over 80%) of components fit the noise model, particularly with motion (mean=64%). A mean 25% fit Phys_Freq Model (RETROICOR) and the Phys_Variability model (RVT & HRT). This indicates that ICA doesn't cleanly separate signal from noise. Dashed lines are means

CONCLUSIONS

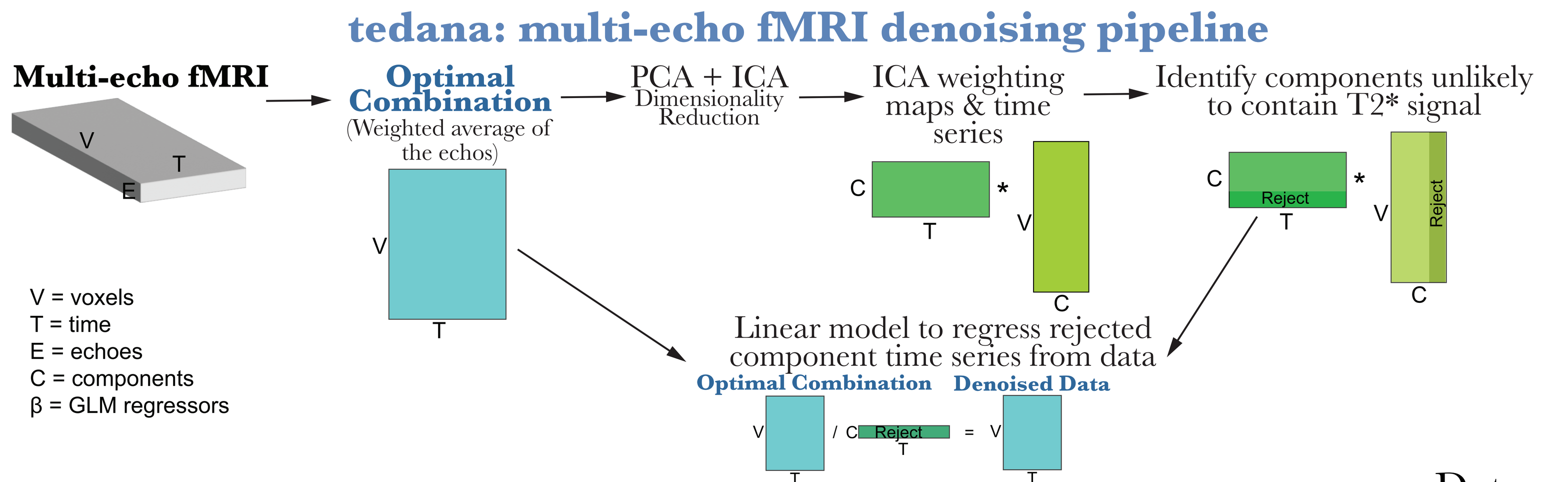
- The combined regressors method, while conserving degrees of freedom, produced results that were slightly inferior in noise elimination to tedana for the word-nonword contrast & neural with the visual-audio contrast.
- Possible reasons combined regressors are worse:
  - Task-correlated breathing and motion are artifacts & should be removed
  - Combined regressors remove components that are a mix of desired signal and noise
  - Most ICA components (often over 80%) correlate with the noise regressors. ICA does not cleanly separately signal and noise into distinct components

FUTURE STEPS

- Explore alternatives to ICA that take advantage of multi-echo information to cleanly separate signal
- Examine individual participants with low and high levels of motion to better characterize factors that affect tedana and the combined regressors results
- Process breathing & movie runs to see how combined regressors directly address respiratory artifacts
- Integrate NORDIC[11] into this processing stream

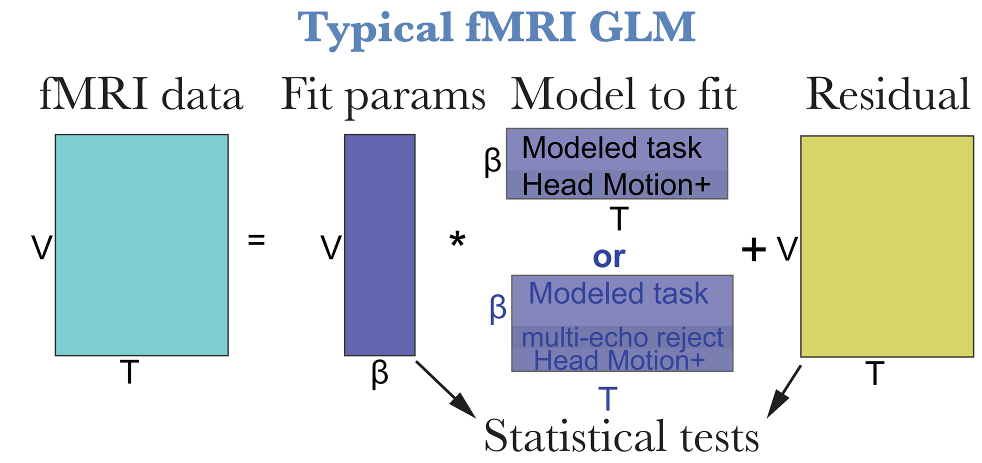
DENOISING METHODS

tedana: multi-echo fMRI denoising pipeline



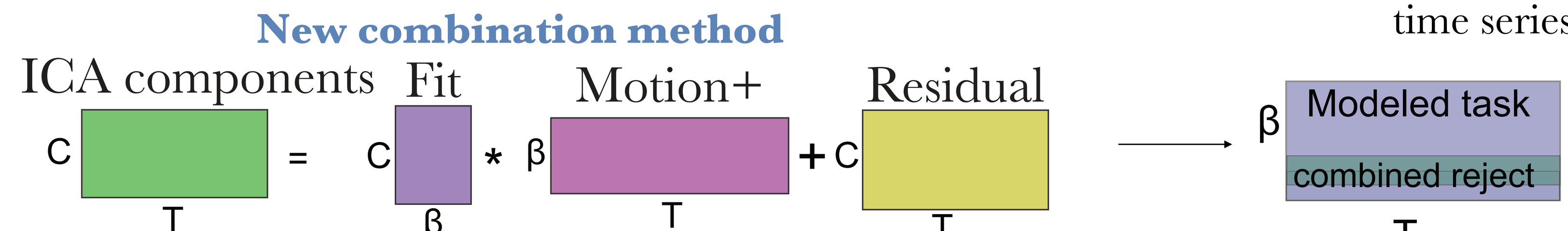
Identify ICA components to rejected as not T2* and linearly regress the time series of those components from the data

Typical fMRI GLM



Data are fit to a model that contains both expected behavioral responses & nuisance regressors (Per run in this study: 4 detrending, 12 motion, 3 ventricles). Tedana denoising adds the time series from rejected components as nuisance regressors

New combination method



Find ICA components that are significantly modeled by motion, respiratory, and cardiac frequencies[6], respiratory volume[1], and heart rate variability[8] over time. Using $p<0.05_{bonf}$ & $R^2>0.5$ as the threshold. This is conceptually similar to AROMA[9], but benefits from multi-echo information

Get one combined set of nuisance regressors using both models.

Benefits & Risks for combined method

\+ Combined regressors give a lot of flexibility for ways to combine empirical noise models

\- Works best if each ICA component is a clean model signal or noise