Optimizing Data Decomposition Methods for Multi-Echo fMRI Denoising

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INTRODUCTION

- Independent Component Analysis (ICA) is used to denoise multi-echo fMRI data by removing non-neural signal and can result in better quality data in less acquisition time[1,2]
- ICA separates data into statistically independent spatial components
- Theoretically, the optimal number of components is the true number of statistically independent sources or dimensions that contribute to total signal
- Over-separation of signal can lead to loss of statistical power from overfitting, while under-separation of signal can make it hard to correctly remove artifacts
- Established dimensionality estimation methods sometimes fail, but each uses different criteria, so we tested whether any commonly used algorithms offered consistent and reliable estimates
- Given that the true dimension is difficult to estimate, we then set aside dimensionality estimation and tested a range of component numbers against a practical definition of optimal: improved contrast-to-noise ratio in task-relevant areas with minimal statistical cost

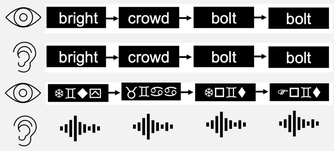
Central Questions

Do dimensionality estimation methods for fMRI agree? How does dimension affect denoising quality?

METHODS

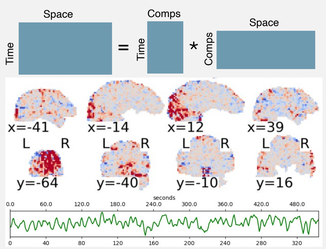
Data Collection and Task Paradigm

- Collected multi-echo fMRI data (Siemens Prisma 3T; TR=1.5s; 3mm^3 voxels, TEs=13.44, 31.7, & 49.96ms) from 25 subjects
- Subjects completed a visual or audio, word or non-word (VA-WNW) discrimination task[3] (3 8.5 min runs) and a paced breathing task with or without movie viewing (2-3 8 min runs)



Task design for VA-WNW discrimination task: 4s per trial, 48 trials per run in an event-related design

ICA and Dimensionality Estimation Methods

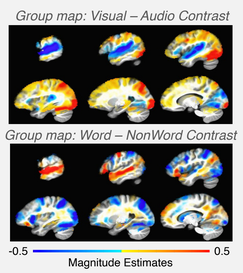


ICA decomposition equation and sample ICA component

- Tested dimensionality estimation methods from MAPCA[1,4] (implemented in tedana) and MELODIC[5] (an FSL fMRI ICA tool) and a modified bootstrapping method (BSA[6])
- Methods from MELODIC and MAPCA optimize a cost function that relates noise variance to singular value decomposition (SVD) with various number of components *(n)*
- BSA compares the stability of SVD components on real and bootstrapped data versus noise
- Compared dimensionality estimates from each method on all runs of data from both tasks

ICA Denoising in Task-Relevant Regions

- The VA-WNW task paradigm was fit to the data with no ICA denoising using a GLM
- Significant voxels in predefined anatomical regions of interest were used to create subject-specific regions of interest (ROIs)
- Data were denoised with tedana using between 20 and 200 components
- For all models, model fit quality was assessed within each ROI using median Fisher Z scores, F statistics, and p-values



RESULTS

Comparing Current Dimensionality Estimate Algorithms

- No method offers reliable and plausible dimensionality estimates across all data
- For each method, estimates for runs within the same dataset fell within a wide range (1a)
- All methods gave some implausibly low (less than 15% of total timepoints) or implausibly high (more than 60% of total timepoints) estimates
- For a single run of data, estimates from different methods varied (1b,c)
- Similar trends are observable across VA-WNW, paced breathing, and movie runs, indicating spread is not due to different numbers of components for different tasks

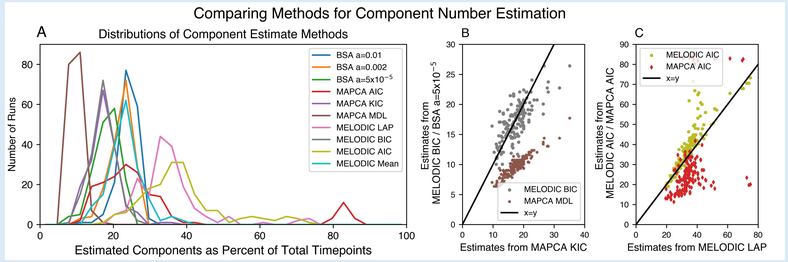
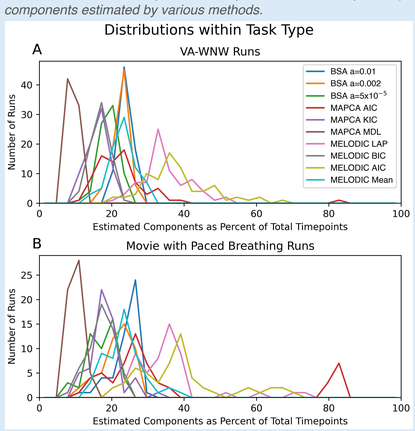


Fig 1. Discrepancies between component number estimates made with various established methods. (a) Histograms show the estimated number of components as a percent of total timepoints. (b,c) Scatterplots show the relationship between percent components estimated by various methods.



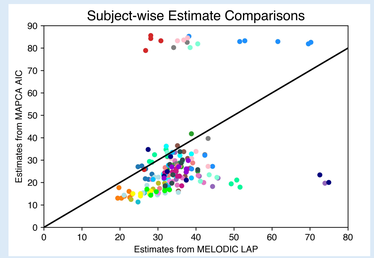


Fig 2. (Left) Discrepancies between component estimates are not driven by task differences. (a) Histograms from the VA-WNW task indicate similar patterns as Fig. 1a, (b) Histograms from the movie with paced breathing task show similar patterns as Fig. 1a. Paced breathing task (not included) shows same pattern.
Fig 3. (Above) Scatterplot of estimates from MELODIC LAP and MAPCA AIC, colored by subject. While some subject-specific clusters appear, outliers are seen in many subjects.

Measuring the Effect of Component Number on Denoising Quality in ROIs

- Fisher Z scores, a measure of contrast-to-noise ratio (CNR), showed a positive association between number of components and CNR in most task-related ROIs (2a,d)
- F statistics and log(p-values) had local maxima in A1 in Visual - Audio contrast, but all values were well beyond the threshold for statistical significance (2b,c)
- F statistics and log(p-values) were fairly stable as number of components increased, the test statistics did not degrade despite loss of degrees of freedom from additional components (2b,c,e,f)
- Across subjects and regions, the statistical measures show that choices of n between 20% and 50% of total timepoints (60-150 components) have little effect on data quality

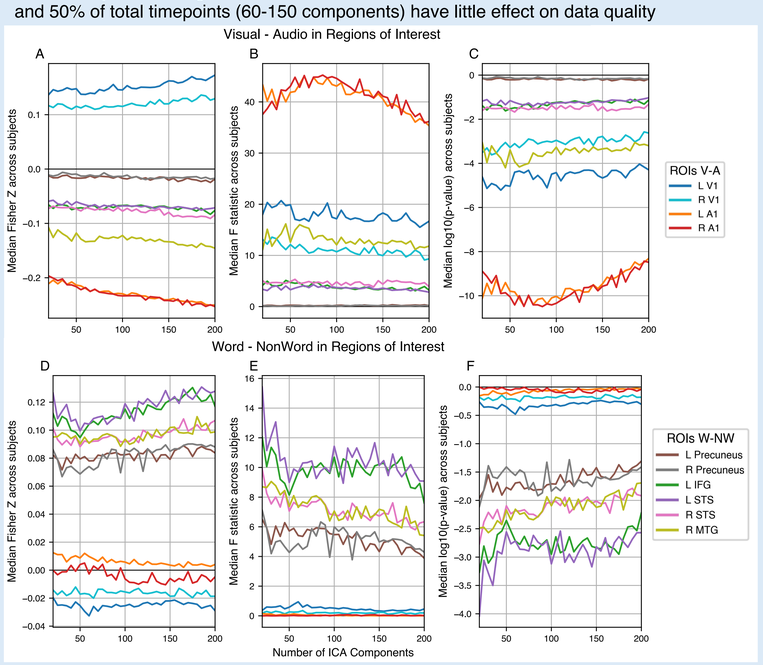


Fig 4. Statistics from tedana denoising run on data from the VA-WNW discrimination task with 20-200 components. Statistical measures of (a-c) visual - audio contrast across ROIs (effects expected in V1 and A1) and (d-f) word - nonword contrast across ROIs (effects expected in STS, IFG, MTG, Precuneus). (a,d) Median Fisher Z values indicate a positive association between n and CNR, (b,e) median F statistics and (c,f) median log(p-values) did not degrade.

CONCLUSIONS

- Dimensionality estimates vary widely within and across methods
- As dimension increases, CNR increases in some ROIs and statistics are relatively stable in most ROIs, despite a decrease in degrees of freedom
- Ongoing work examines several ways to improve multi-echo data decomposition and denoising

Key Takeaways

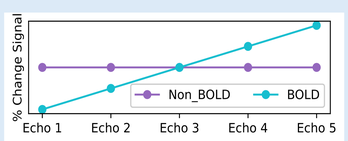
Current methods make inconsistent dimensionality estimates

ICA denoising quality is relatively stable for a wide range of dimensions

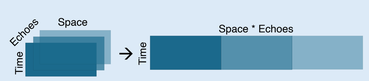
ONGOING WORK

Echo-informed Decomposition

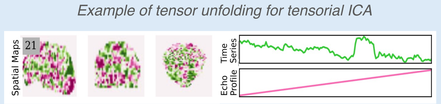
- Denoising can be improved by better decomposition methods or better inclusion/exclusion criteria
- MRI physics dictates how BOLD and non-BOLD signal should decay across echoes, which can inform decomposition and inclusion/exclusion criteria



Simplified BOLD vs non-BOLD echo profiles



Example of tensor unfolding for tensorial ICA



Sample component from Tensorial ICA with 30 Components

- Tensorial ICA approaches take advantage of all echoes in the component creation process and output components with an additional "echo profile" dimension
- Current fMRI tensorial ICA methods[5,7] do not consider physical properties in component creation

Physically-informed Thermal Null

- BSA methods[6] select component number by comparing components from real data with components from Gaussian noise
- Noise scans (with no RF excitation) better estimate a null condition, and may create a more robust stability threshold for determining number of components

Increasing Echoes to Improve Decay Curve Estimate

- Collecting more echoes provides more data to estimate signal decay
- A better estimate of signal decay may allow for more precise denoising that depends less on grouping data (across space or time) to increase the robustness of measured signal

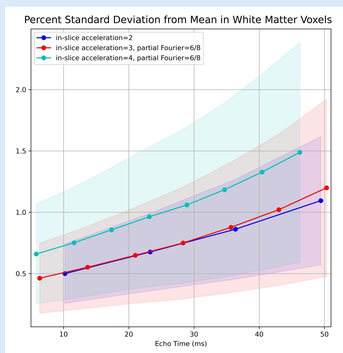


Figure 5. Tradeoffs associated with collecting shorter echo times. Increased acceleration was used to collect shorter echoes but leads to additional measurement noise.

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Marlene Smith is currently applying to grad school
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