What is the Optimal Number of Independent Components for Multi-Echo fMRI Denoising?

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INTRODUCTION

- Independent Component Analysis (ICA) is used to denoise multi-echo fMRI data[1,2] by removing non-neural signal and can result in better quality data in less acquisition time
- ICA separates data into statistically independent spatial components
- The number of components or dimensions (n) should be set by intrinsic properties of the data, but established dimensionality estimation methods don't reliably work on fMRI data

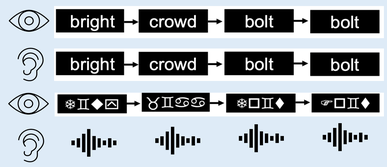
Central Questions

1. Is there a reliable & plausible dimensionality estimation method for fMRI?
2. How does dimension affect denoising quality?

METHODS

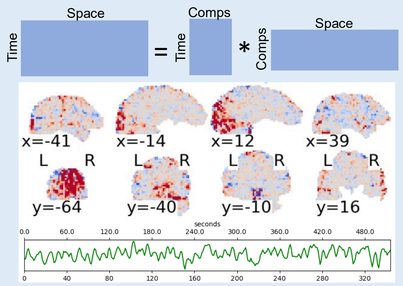
Data Collection and Task Paradigm

- 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 Estimate Methods



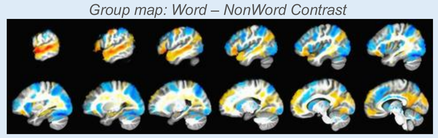
ICA decomposition equation and sample ICA component

- Tested dimensionality estimation methods from MAPCA[1,4] (implemented in tedana) and MELODIC[5] (another common 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 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

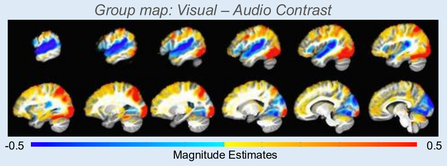
ICA Denoising in Task-Relevant Regions

- The VA-WNW task paradigm was fit to the data with no ICA denoising
- Significant voxels in predefined anatomical ROIs were used to create subject-specific ROIs
- Data were denoised with tedana using component numbers between 20 and 200
- Model fit quality was assessed within each ROI using median Fisher Z scores, F statistics, and p-values

Group map: Word – NonWord Contrast



Group map: Visual – Audio Contrast



REFERENCES

1. DuPre E, Salo T, Ahmed Z, et al. TE-dependent analysis of multi-echo fMRI with tedana. *J Open Source Softw.* 2021;6(66):3669. doi: 10.21105/joss.03669
2. Kundu P, et. al. "Differentiating BOLD and non-BOLD signals in fMRI time series using multi-echo EPI" *NeuroImage*. 2012;60(3):1759-70. doi: 10.1016/j.neuroimage.2011.12.028
3. Malins JG, Gumkowski N, Buis B, et al. Dough, Tough, Cough, Rough: A "fast" fMRI Localizer of Component Processes in Reading. *Neuropsychologia*. 2016;91:394–406. doi: 10.1016/j.neuropsychologia.2016.08.027
4. Li YO, Adali T, Calhoun VD. Estimating the number of independent components for functional magnetic resonance imaging data. *Hum Brain Mapp*. 2007;28(11):1251–1266. doi: 10.1002/hbm.20359
5. Beckmann CF, Smith SM. Probabilistic Independent Component Analysis for Functional Magnetic Resonance Imaging. *IEEE Trans Med Imaging*. 2004;23(2):137-152. doi: 10.1109/TMI.2003.822821
6. Majeed W, Avison MJ. Robust Data Driven Model Order Estimation for Independent Component Analysis of fMRI Data with Low Contrast to Noise. *PLoS One*. 2014;9(4):e94943. doi: 10.1371/journal.pone.0094943

RESULTS

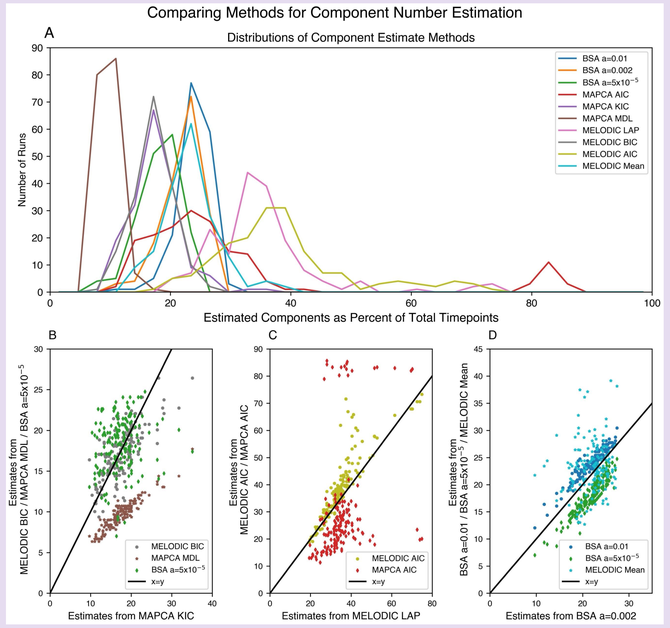


Fig 1. Discrepancies between component number estimates made with various established methods. (a) Histograms show the estimated number of components as a percent of total timepoints. (b-d) Scatterplots show the relationship between percent components estimated by various methods.

Comparing Current Dimensionality Estimate Algorithms

- Component number estimates varied across methods
- 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–d)
- No method offers reliable and plausible dimensionality estimates across all data

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, showing little effect on statistical power despite loss of degrees of freedom (2b,c,e,f)
- Across subjects and regions, the statistical measures show that choices of n between 20% and 50% of total timepoints (n = 60-150) have little effect on data quality

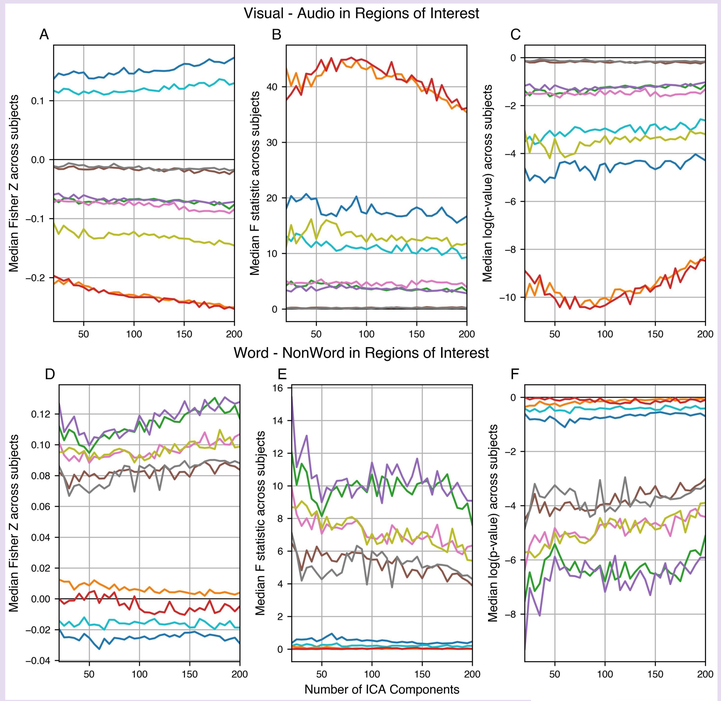


Fig 2. Statistics from tedana denoising run on data from the VA-WNW discrimination task with 20-200 components. Statistical measures of (a-c) visual - audio contrast across ROIs (effects expected in V1 and A1) and (d-f) word - nonword contrast across ROIs (effects expected in STS, IFG, MTG, Precuneus). (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) show little effect on statistical power.

CONCLUSIONS

- Dimensionality estimates vary widely within and across methods
- As dimension increases, CNR increases in some ROIs
- Statistical power is relatively stable in most ROIs, despite a decrease in degrees of freedom

Key Takeaways

1. Current methods make inconsistent dimensionality estimates
2. ICA denoising quality is relatively stable for a wide range of dimensions

FUTURE DIRECTIONS

- Future work will explore alternative approaches to denoising multi-echo fMRI data either via better decomposition methods or better inclusion/exclusion criteria
- Tensor ICA may better separate data into components
- Echo profiles might help identify components that contain neural versus non-neural signal

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