Dataset 1A: Single Model Demo

- Acquisition parameters: 3T Siemens Prisma scanner
  - BOLD: TR = 2100 ms, echo times = 13.0, 29.4, and 45.7 ms, voxel size = 3 × 3 × 3 mm3, acceleration factor = 2

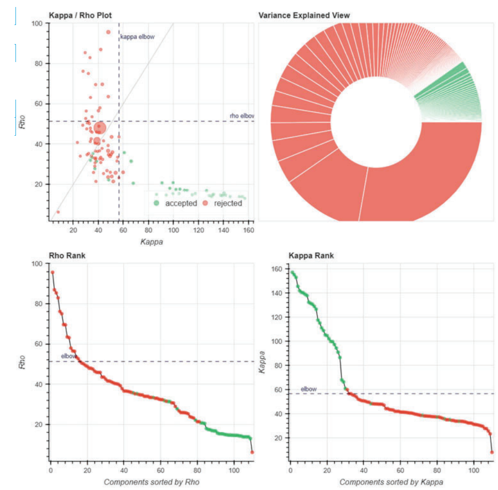
- External Regressors Used:
  - Motion: x, y, z, roll, pitch, yaw
  - Cardiac (+3 derivs; Chang et al., 2009)
  - Respiratory (+3 derivs: Birn et al., 2008)

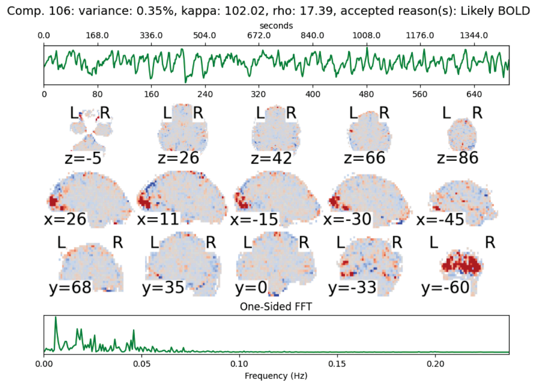
- Command Line Prompt:

tedana -d *echo_1.nii.gz echo_2.nii.gz echo_3.nii.gz* -e *13 29.4 45.7* --mask *autoMask.nii* --out-dir *test_sub_006* --tree *tedana\resources\decision_trees\demo_external_regressors_single_model.json* --external *test_sub_006\external_regressors.txt* --verbose --debug

TEDANA 24.0.2.DEV97+GBE89F1E Reporting documentation

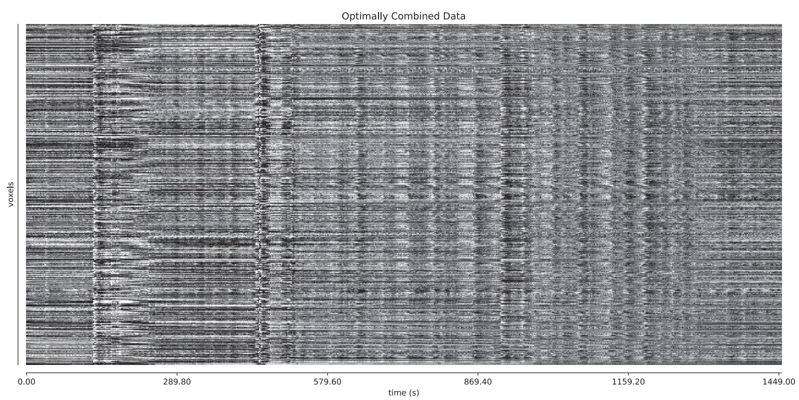
ICA components



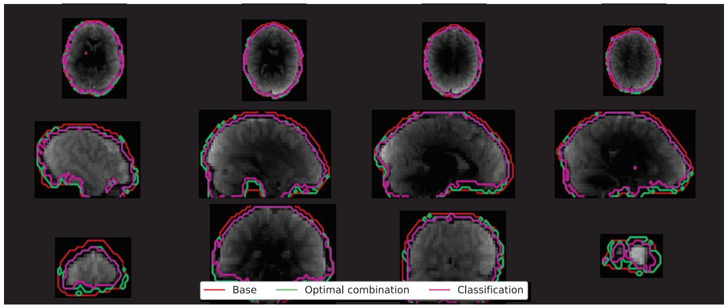


Carpet plots

Optimally combined | Denoised | Accepted | Rejected



Adaptive mask

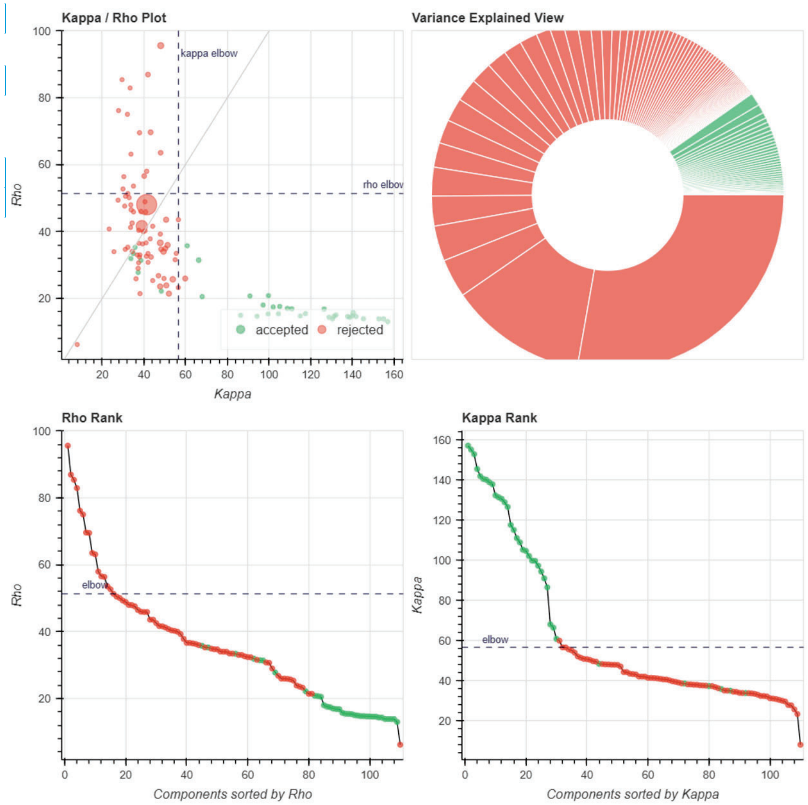


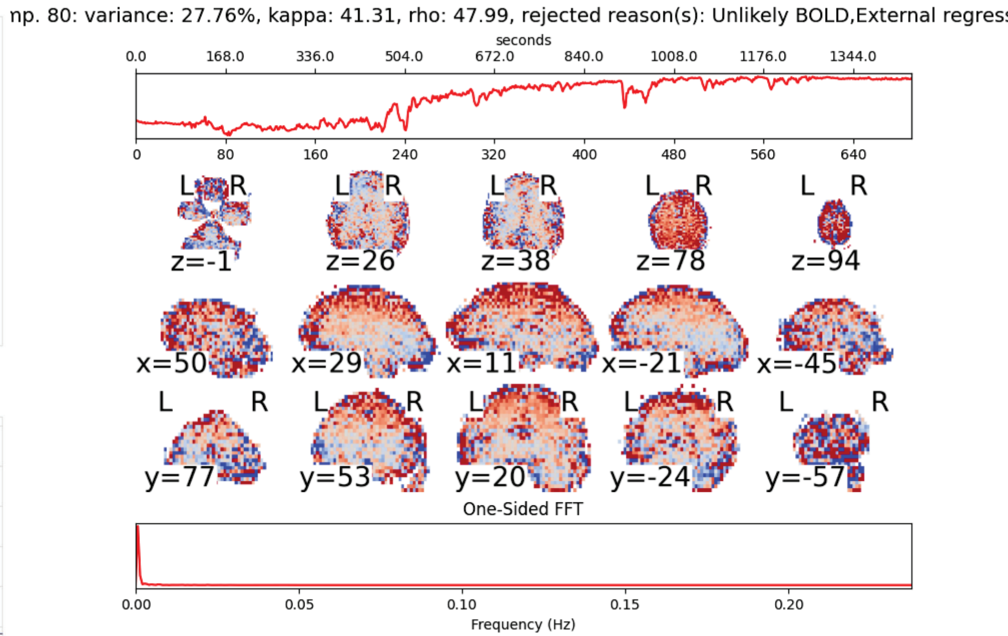
T2* and S0

T2*

TEDANA 24.0.2.DEV97+GBE89F1E Reporting documentation

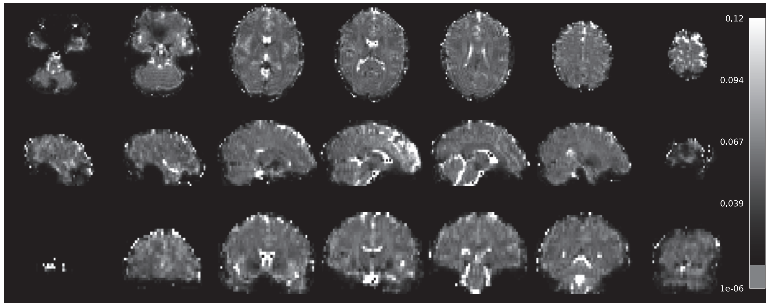
ICA components

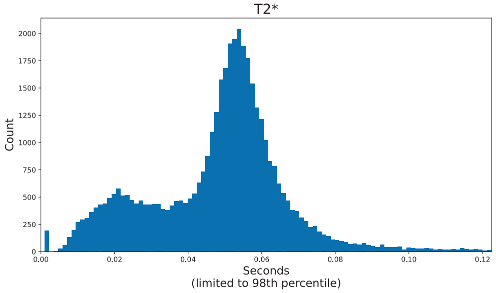




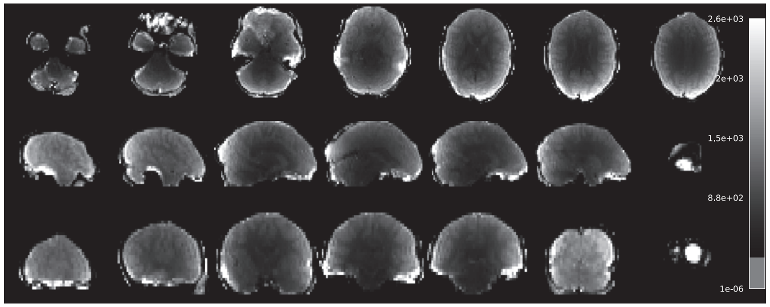
Carpet plots

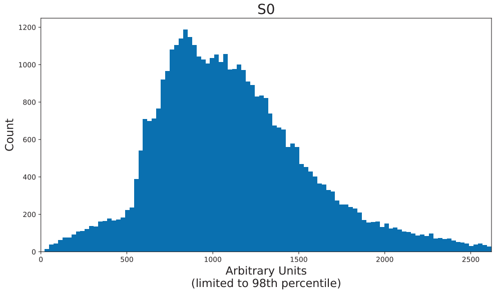
Optimally combined Denoised Accepted Rejected



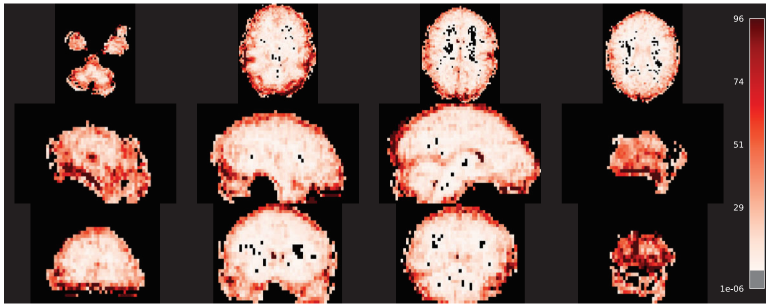


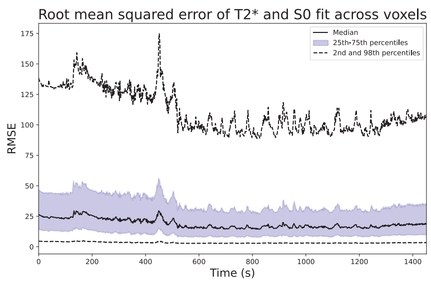
S0





T2* and S0 model fit (RMSE). (Scaled between 2nd and 98th percentiles)





Info

Tedana command used:

```
tedana -d C:\Users\segoo\Documents\tedana\test_subjects\test_sub_7_13\echo1_dr_mo_st.nii C:\Users\segoo\Documents\tedana\test_subjects\test_sub_7_13\echo2_dr_mo_st.nii
C:\Users\segoo\Documents\tedana\test_subjects\test_sub_7_13\echo3_dr_mo_st.nii -e 13 29.4 45.7 --mask C:\Users\segoo\Documents\tedana\test_subjects\test_sub_7_13\autoMask.nii --out-dir
C:\Users\segoo\Documents\tedana\test_subjects\test_sub_7_13\ --tree C:\Users\segoo\Documents\tedana\tedana\tedana\resources\decision_trees\demo_external_regressors_single_model.json --
external C:\Users\segoo\Documents\tedana\test_subjects\test_sub_7_13\external_regressors.txt --verbose --debug
```

System:	Windows
Node:	Sarah_Laptop
Release:	10
System version:	10.0.22631
Machine:	AMD64
Processor:	Intel64 Family 6 Model 141 Stepping 1, GenuineIntel
Python:	3.11.9 (tags/v3.11.9:de54cf5, Apr 2 2024, 10:12:12) [MSC v.1938 64 bit (AMD64)]
Tedana version:	24.0.2.dev97+gbe89f1e
Other library versions:	{'bokeh': '3.4.1', 'mapca': '0.0.5', 'matplotlib': '3.9.1', 'nibabel': '5.2.1', 'nilearn': '0.10.4', 'numpy': '1.26.4', 'pandas': '2.2.2', 'scikit-learn': '1.4.2', 'scipy': '1.13.0', 'threadpoolctl': '3.5.0'}

About tedana

This is based on the minimal criteria of the original MEICA decision tree (Kundu et al. 2013) without the more aggressive noise removal steps (DuPre et al. 2021). TE-dependence analysis was performed on input data using the tedana workflow (DuPre et al. 2021). A user-defined mask was applied to the data. An adaptive mask was then generated using the dropout method(s), in which each voxel's value reflects the number of echoes with 'good' data. An adaptive mask was then generated using the dropout method(s), in which each voxel's value reflects the number of echoes with 'good' data. A two-stage masking procedure was applied, in which a liberal mask (including voxels with good data in at least the first echo) was used for optimal combination, T2*/S0 estimation, and denoising, while a more conservative mask (restricted to voxels with good data in at least the first three echoes) was used for the component classification procedure. A monoexponential model was fit to the data at each voxel using log-linear regression in order to estimate T2* and S0 maps. For each voxel, the value from the adaptive mask was used to determine which echoes would be used to estimate T2* and S0. Multi-echo data were then optimally combined using the T2* combination method (Posse et al. 1999). Principal component analysis based on the PCA component estimation with a Moving Average(stationary Gaussian) process (Li et al. 2007) was applied to the optimally combined data for dimensionality reduction. The following metrics were calculated: kappa, rho, countnoise, countsigFT2, countsigFS0, dice_FT2, dice_FS0, signal-noise_t, variance explained, normalized variance explained, d_table_score. Kappa (kappa) and Rho (rho) were calculated as measures of TE-dependence and TE-independence, respectively. A t-test was performed between the distributions of T2*-model F-statistics associated with clusters (i.e., signal) and non-cluster voxels (i.e., noise) to generate a t-statistic (metric signal-noise_z) and p-value (metric signal-noise_p) measuring relative association of the component to signal over noise. The number of significant voxels not from clusters was calculated for each component. Independent component analysis was then used to decompose the dimensionally reduced dataset. The following metrics were calculated: R2stat nuisance model, countsigFS0, countsigFT2, dice_FS0, dice_FT2, kappa, normalized variance explained, pval nuisance model, rho, signal-noise_t, variance explained. Kappa (kappa) and Rho (rho) were calculated as measures of TE-dependence and TE-independence, respectively. A t-test was performed between the distributions of T2*-model F-statistics associated with clusters (i.e., signal) and non-cluster voxels (i.e., noise) to generate a t-statistic (metric signal-noise_z) and p-value (metric signal-noise_p) measuring relative association of the component to signal over noise. {'External nuisance regressors that fit to components using a linear model were rejected.'}

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References

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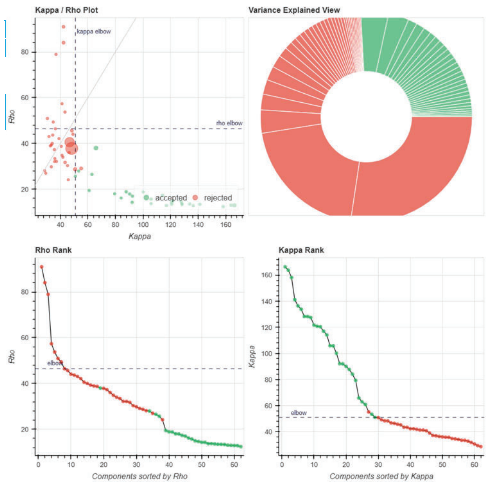
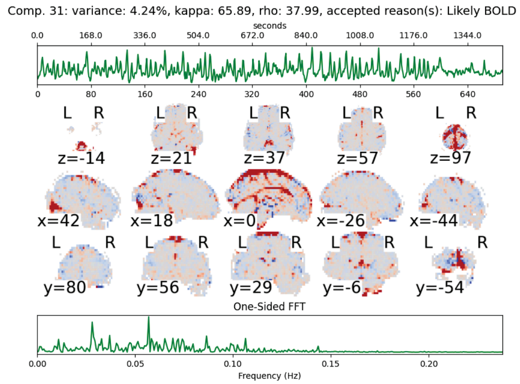
TEDANA 24.0.2.DEV97+GBE89F1E   Reporting documentation

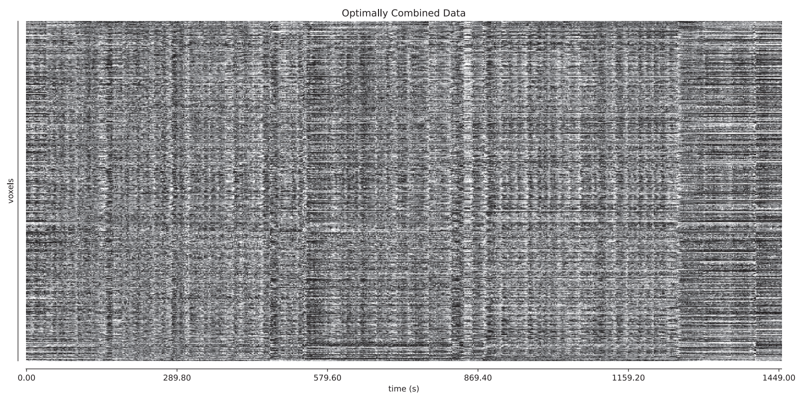
ICA components



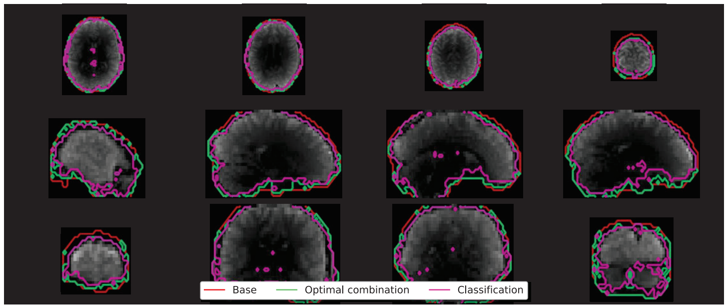


Carpet plots

Optimally combined   Denoised   Accepted   Rejected



Adaptive mask

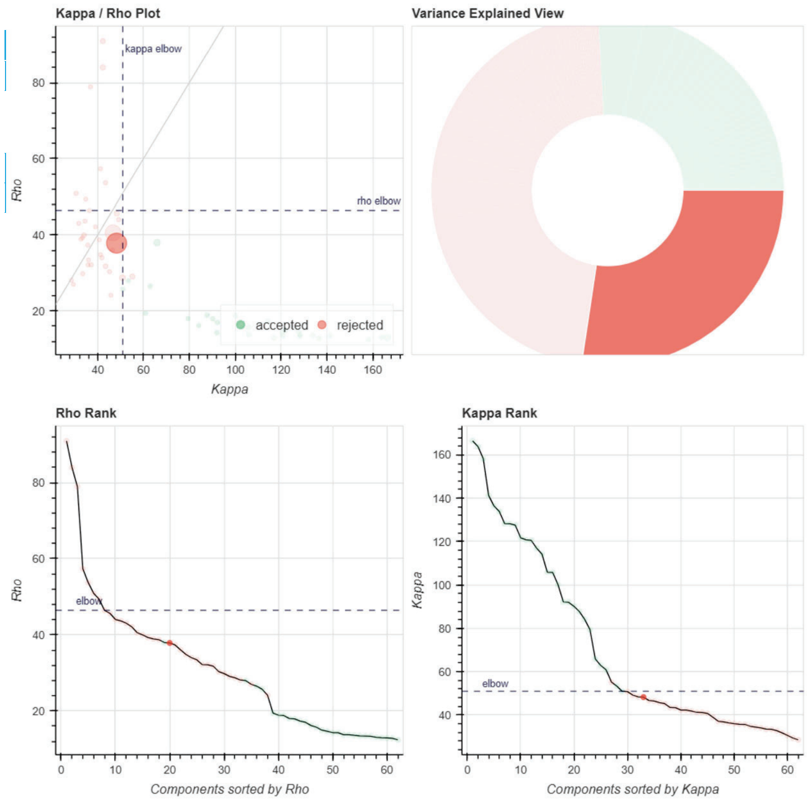


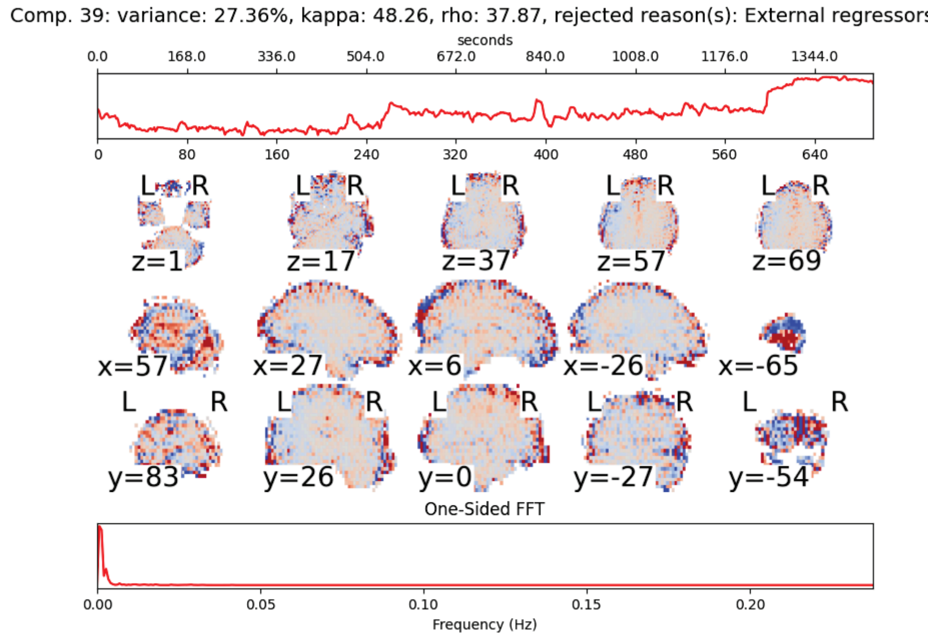
T2* and S0

T2*

TEDANA 24.0.2.DEV97+GBE89F1E Reporting documentation

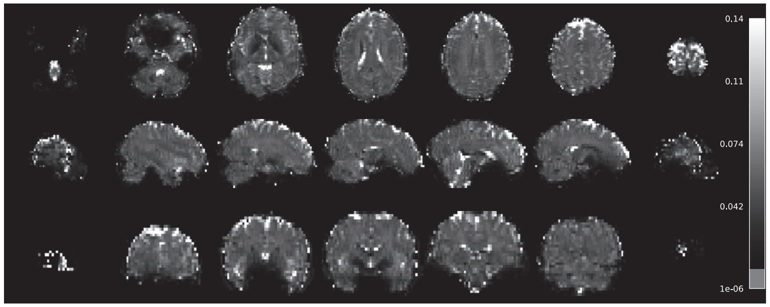
ICA components

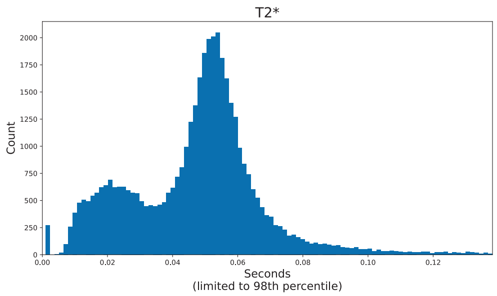




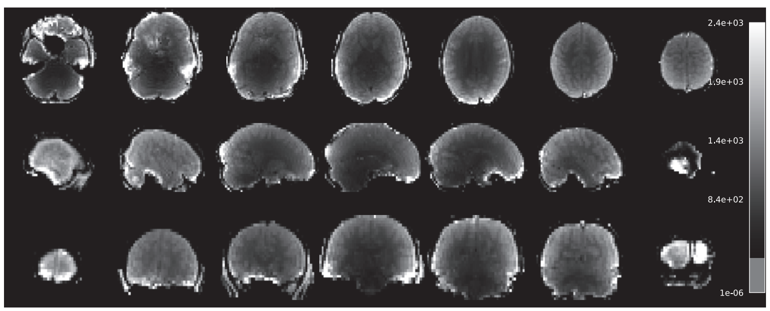
Carpet plots

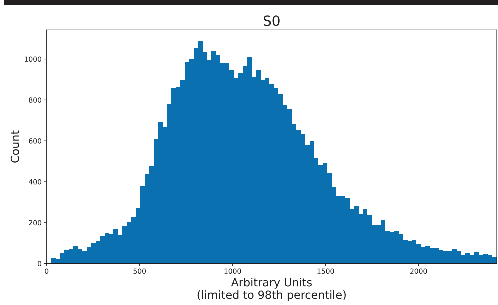
Optimally combined Denoised Accepted Rejected



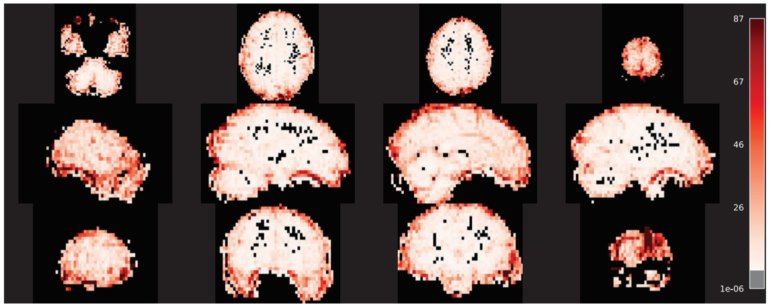


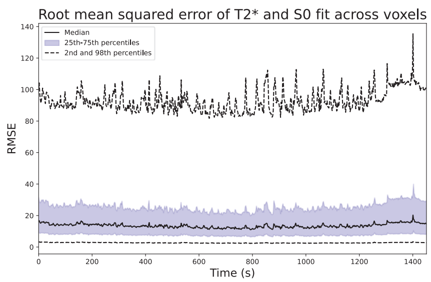
S0





T2* and S0 model fit (RMSE). (Scaled between 2nd and 98th percentiles)





Info

Tedana command used:

```
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C:\Users\segoo\Documents\tedana\test_subjects\test_sub_6_19\echo3_dr_mo_st.nii -e 13 29.4 45.7 --mask C:\Users\segoo\Documents\tedana\test_subjects\test_sub_6_19\autoMask.nii --out-dir
C:\Users\segoo\Documents\tedana\test_subjects\test_sub_6_19\ --tree C:\Users\segoo\Documents\tedana\tedana\tedana\resources\decision_trees\demo_external_regressors_single_model.json --
external C:\Users\segoo\Documents\tedana\test_subjects\test_sub_6_19\external_regressors.txt
```

System:	Windows
Node:	Sarah_Laptop
Release:	10
System version:	10.0.22631
Machine:	AMD64
Processor:	Intel64 Family 6 Model 141 Stepping 1, GenuineIntel
Python:	3.11.9 (tags/v3.11.9:de54cf5, Apr 2 2024, 10:12:12) [MSC v.1938 64 bit (AMD64)]
Tedana version:	24.0.2.dev97+gbe89f1e
Other library versions:	{'bokeh': '3.4.1', 'mapca': '0.0.5', 'matplotlib': '3.9.1', 'nibabel': '5.2.1', 'nilearn': '0.10.4', 'numpy': '1.26.4', 'pandas': '2.2.2', 'scikit-learn': '1.4.2', 'scipy': '1.13.0', 'threadpoolctl': '3.5.0'}

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References

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