Comparison of multi-subject ICA methods for analysis of fMRI data

Abstract No:

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Introduction:

Spatial independent component analysis (ICA) applied to fMRI data identifies functionally connected networks by estimating spatially independent patterns from their linearly mixed fMRI signals. Several multi-subject ICA approaches estimating subject-specific time courses (TCs) and spatial maps (SMs) have been developed together with PCA reduction strategies, however there has not yet been a full comparison of the implications of their use.

Here, we provide extensive comparisons of three data reduction methods and four multi-subject ICA approaches using simulated and fMRI task data. We compare subject-specific, spatial concatenation, and group data mean subject-level reduction strategies using PCA and probabilistic PCA (PPCA). We compare three direct back-reconstruction group ICA approaches (GICA1-GICA3) and an indirect back-reconstruction approach, spatio-temporal regression (STR, or dual regression). All are in GIFT for Matlab (http://icatb.sourceforge.net/).

Methods:

Subject-level PCA methods: Subject-specific reduces each subject; spatial concatenation obtains a PCA reducing matrix on the spatially-concatenated data, then applies that reduction to each subject separately; group data mean obtains a PCA reducing matrix on the mean data matrix, applies that reduction to each subject separately, then additional subject-specific PCA rotation. Finally, the subject-reduced data are time-concatenated and a PCA and ICA is performed on this group data.

Two primary back-reconstruction methods: GICA3, improving the original group ICA (GICA1) (Calhoun, et al. 2001b; Calhoun, et al. 2002), has the desirable properties of the product of the subject-specific TCs and SMs predict the subject data to the accuracy of information retained from PCA, and the sum of the subject-specific SMs is the group map which has an intuitive random effects-like interpretation. STR regresses the original subject data onto the ICA SM to estimate subject-specific TCs, then regresses the subject data onto those TCs to estimate subject-specific SMs, thus the original common SM assumption and the later estimated SMs present a contradiction.

Simulated data has 32 subjects with 8 components (Fig. 1) and the auditory oddball task (AOD) data has 28 healthy controls scanned while detecting an infrequent sound within a series of regular and different sounds (Calhoun, et al. 2008). For the AOD, results for the subject-specific TCs and SMs for two subjects are z-scored and the SMs are thresholded at one and displayed in nine equally-spaced axial slices from 60mm to −20mm. Because the TCs are more complex for the real data, we concentrate on the SMs.

Results:

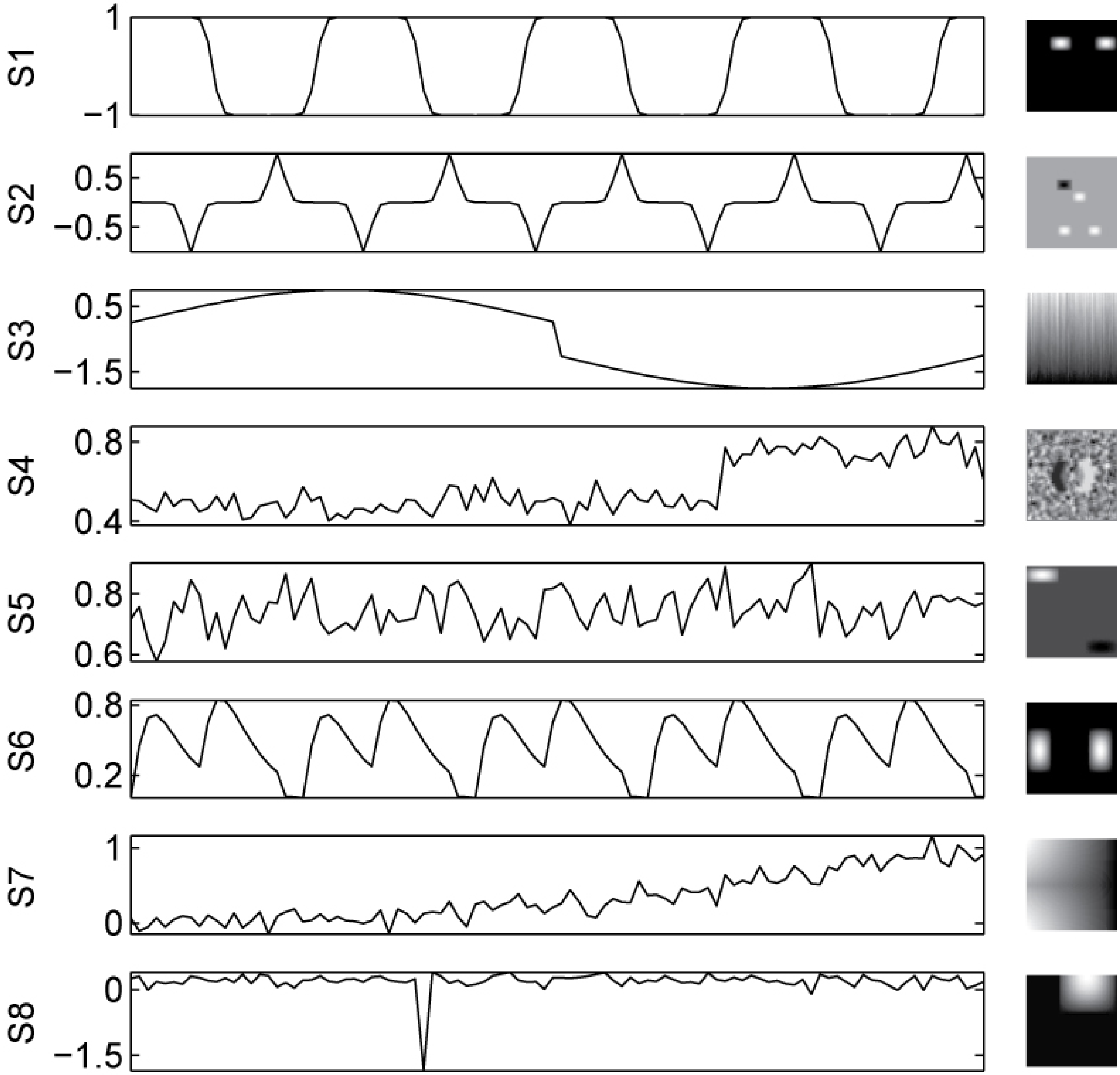
For simulated data, MDL estimated 6 components, and we considered a range of components retained for the PCA at the subject-level (60, 15, 8, 6, 4) and group-level (30, 15, 8, 6, 4). We compare estimated subject-specific TCs and SMs with their true values (Fig. 2). GICA3 with subject-specific subject-level PCA has the lowest RMSE for TCs and SMs. GICA3 has consistently good SMs and GICA1 and STR have consistently good TCs regardless of the subject-level PCA method. Subject-specific and group data mean subject-level PCA methods both have low RMSEs. ICA is best for GICA3 TC and comparable for SMs, while PICA is best for STR TCs and SMs. PICA sometimes failed to converge when the requested number of components was greater (15) than the true number of components (8).

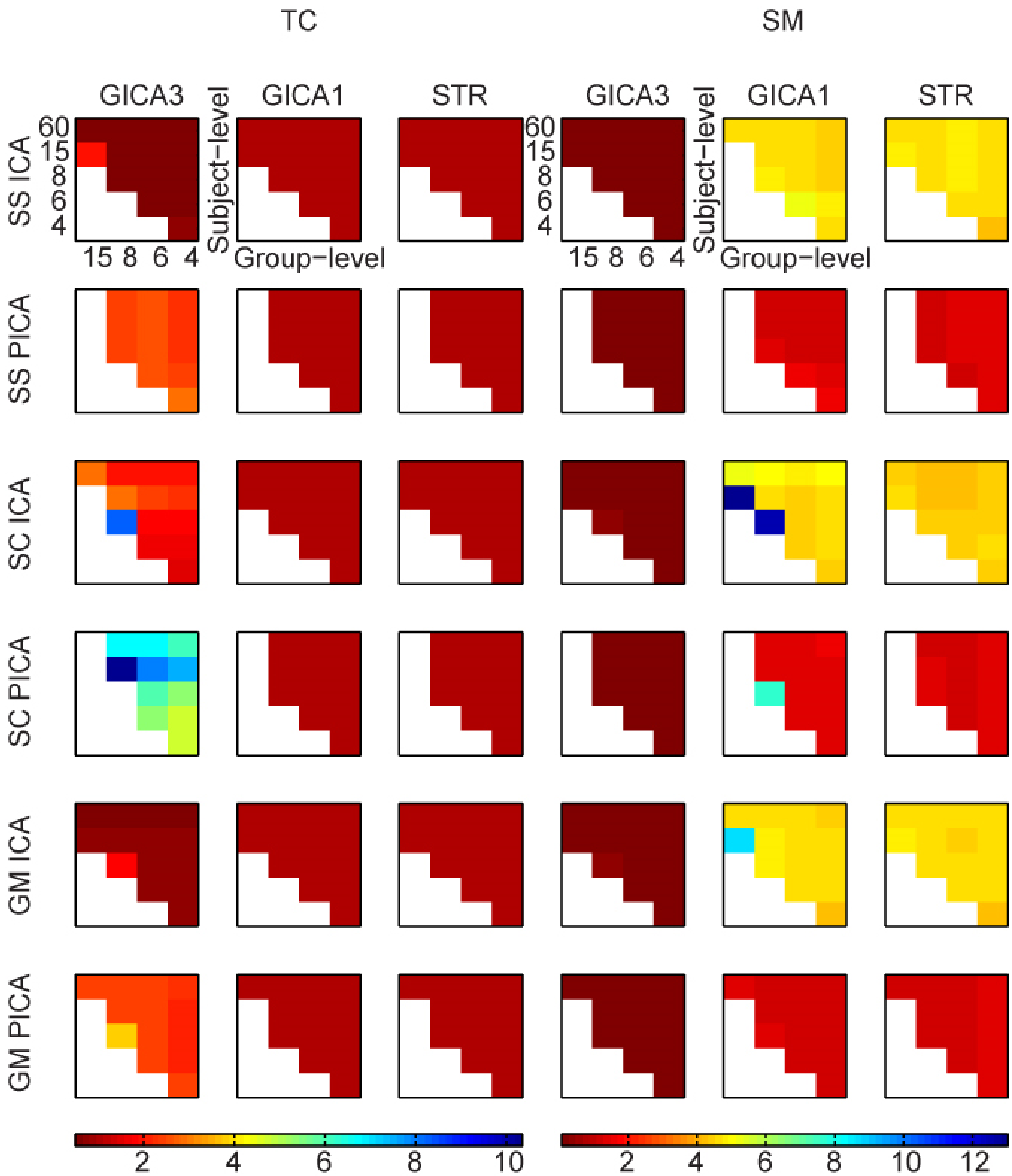
We correlate estimated SMs from GICA3 and STR to select most similarly and most differently estimated subjects for simulated data task-related component (1) (Fig. 3) and AOD task DMN (Fig. 4). For simulated data, the most similar subject (28) has a very clean GICA3 SM while the STR SM has an artifact from component 2, and the difference of GICA3 and STR TCs reveals component 2 associated with the spatial artifact in the SM for STR. For the least similar subject (27) SM activation for GICA3 is stronger than for STR and STR has an artifact from a different component (4), and the difference of GICA3 and STR TC shows the stronger task in GICA3 and the STR step-change artifact of component 4. Thus, GICA3 SMs estimated the true SM well, while STR has artifacts. The AOD default mode network component reveals similar artifacts in STR (Fig. 4). For the most similar subject (24) the difference SM reveals bright red in slices 50 and −10 where STR has negative activation not appearing in GICA3. For the least similar subject (21), the difference SM reveals GICA3 has more DMN activation (slices 50 through 20) while STR has artifacts (slices 10 to −20).

Conclusions:

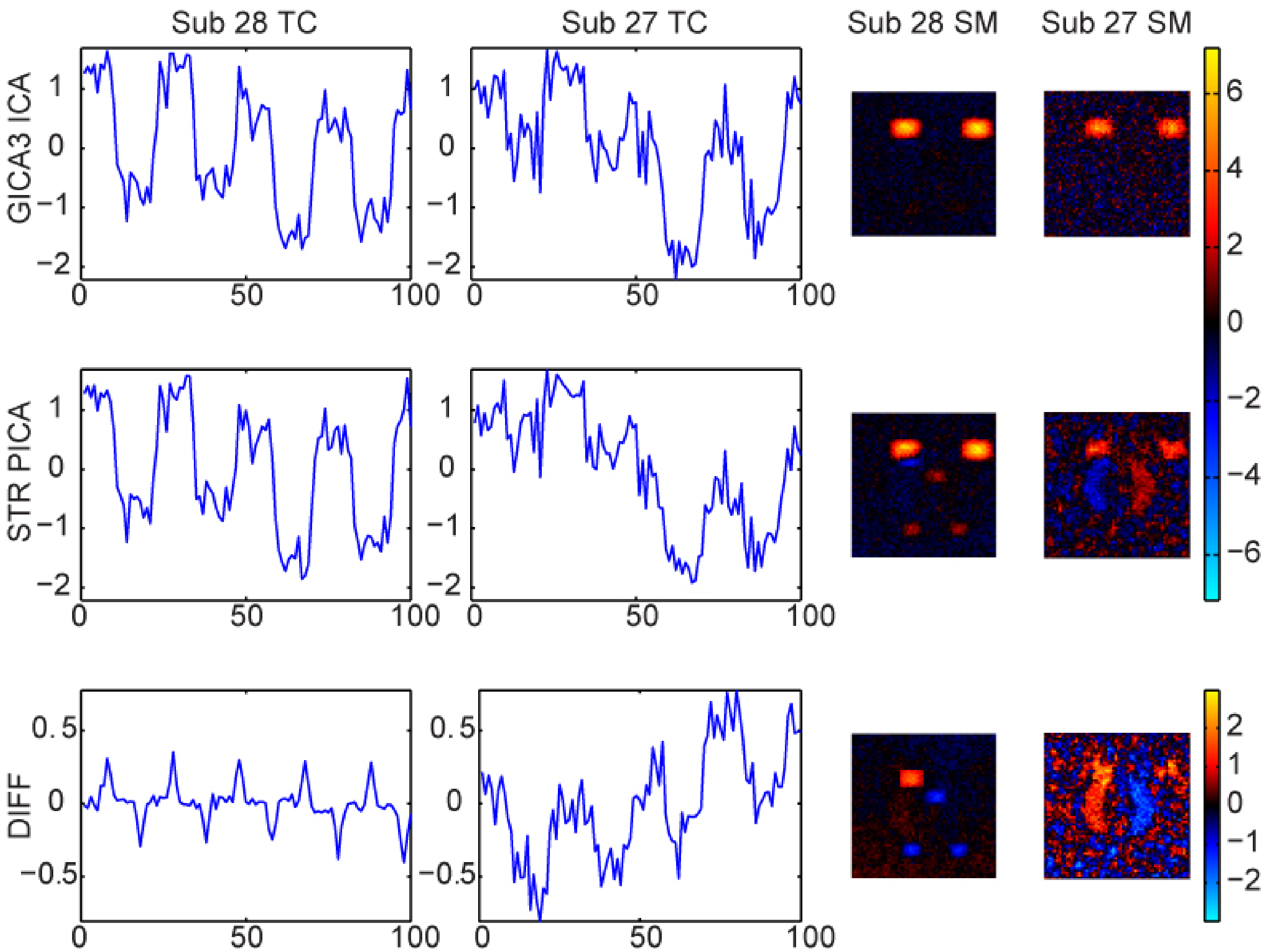
Our evidence-based recommendation is to use GICA3, introduced here, with subject-specific PCA and noise-free ICA, providing robust and accurately estimated SMs and TCs with an intuitive interpretation. GICA3 estimates SMs much more accurately than STR, with comparable TCs. STR requires contradictory assumptions regarding SMs, first assuming a common SM to estimate subject-specific TCs, then distinct subject-specific SMs are estimated. Because component TCs are often correlated to some degree, STR may show ancillary component artifacts in estimated SMs. Results show GICA1 approximates STR, and they are equivalent with no PCA reduction.

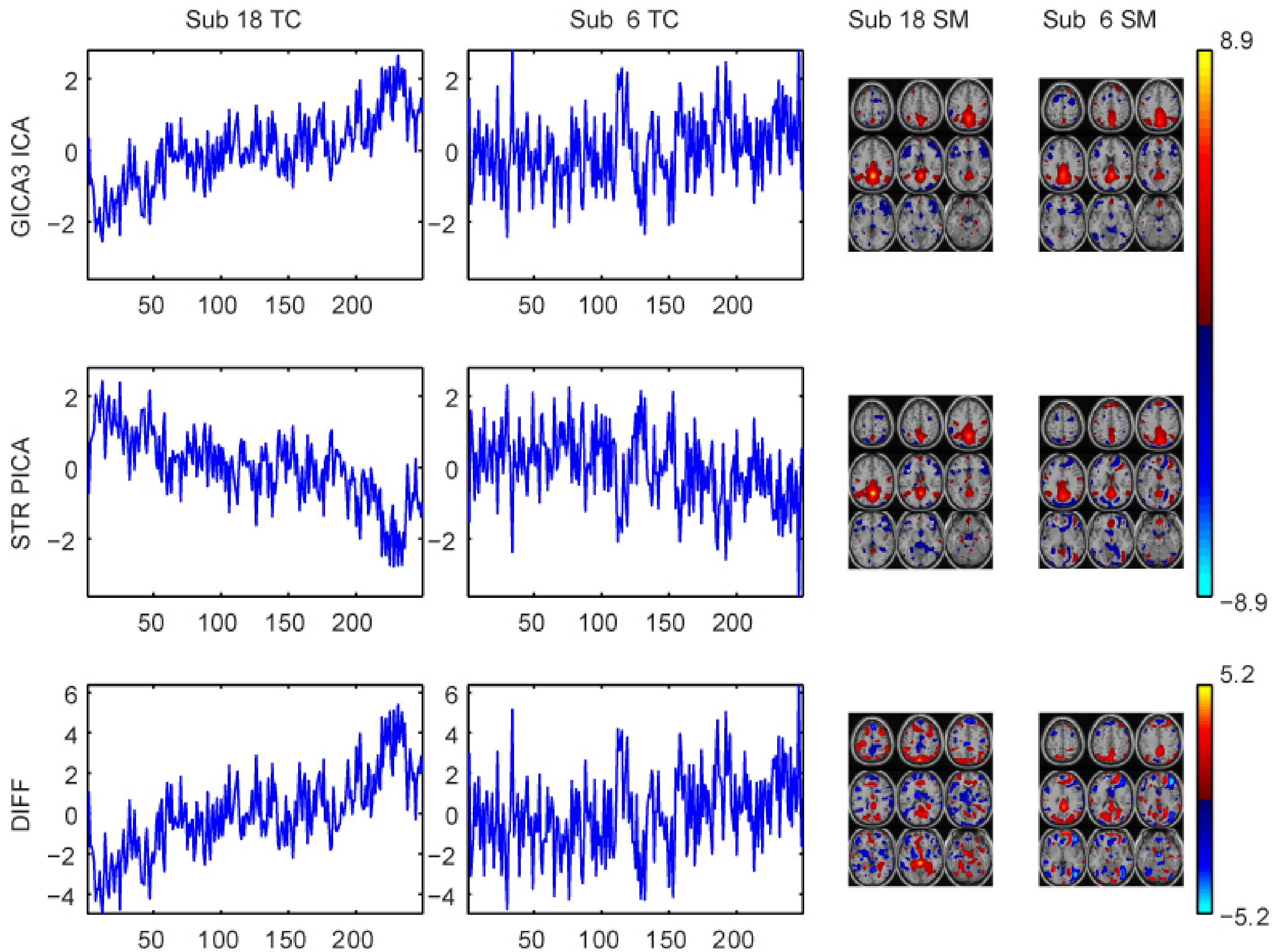
For subject-level PCA, both subject-specific and group data mean are preferred. Noise-free ICA performs better for GICA3, while PICA better for STR. Because subject-specific SMs are more accurately estimated by GICA3 than STR, inference of group spatial activation differences, for example, are also expected to be more accurate using GICA3.





TC
SM
GICA3
GICA1
STR
GICA3
GICA1
STR
Subject−level
Group−level
60
15
8
6
4
15 8 6 4
SS ICA
SS PICA
SC ICA
SC PICA
GM ICA
GM PICA
2
4
6
8
10
2
4
6
8
10
12


Sub 28 TC
Sub 27 TC
Sub 28 SM
Sub 27 SM
GICA3 ICA
STR PICA
DIFF
1
0
−1
−2
0.5
−0.5
0
50
100
6
4
2
−4
−6



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Categories

- Bold fMRI (Modeling and Analysis)
- Multivariate Modeling, PCA and ICA (Modeling and Analysis)