Supporting Information

Generation of Simulation Data

In order to investigate the joint blind source separation(BSS) performance of mCCA+jICA and compare it to that of joint ICA and mCCA, we simulated two types of sources as two features. As shown in Figure S1, eight sources were generated for each feature to simulate images (256 × 256) and one-dimensional signals (1×2000) respectively, resulting in true sources $\mathbf{S}_1$ (in dimension of 8×65536) and $\mathbf{S}_2$ (in dimension of 8×2000). The mixing matrices of each feature, *i.e.* $\mathbf{A}_1$ and $\mathbf{A}_2$ (in dimension of 100×8), had diverse correlations between their corresponding columns, $\mathbf{A}_1$-$\mathbf{A}_2$ correlation = [0.99 0.07 0.36 0.63 0.20 0.23 0.79 0.36], as the ground truth listed in Figure S1.

One hundred noisy mixed images $\mathbf{X}_k$ were generated for each modality under each of the 11 noisy conditions via $\mathbf{X}_k = \mathbf{I}_k + \mathbf{N}_k = \mathbf{A}_k\mathbf{S}_k + \mathbf{N}_k$, k=1, 2; where $\mathbf{I}_k$ was pure signal mixture and $\mathbf{N}_k$ was random Gaussian noise. The corresponding mean peak signal-to-noise ratios (PSNR) were in range of [-1 20] dB. The PSNR is a most commonly used measure of image quality after corruption or recovery, which is defined as (s1) for the j^{th} mixture of feature k at every noisy condition, j=1,2…100. Typical PSNR value for the acceptable image quality is about 30 dB; the lower the value, the more degraded the image (Thomos, et al. 2006).

$$PSNR(k,j) = 10\log_{10}\left[\frac{\max\limits_{i\in[1,\,l]}(\mathbf{I}_k(i))^2}{\frac{1}{l}\sum\limits_{i=1}^{l}|\mathbf{X}_k(i)-\mathbf{I}_k(i)|^2}\right] \qquad j=1,2...100,\, l=\begin{cases}65536, & k=1\\ 2000, & k=2\end{cases} \tag{s1}$$

Three fusion models: jICA, mCCA and mCCA+jICA were implemented on simulated datasets respectively under every PSNR for 10 runs. The decomposed components were paired with the true sources via cross-correlation automatically within each feature. We adopted three metrics to estimate the joint BSS performance:

1) the average correlation of the estimated components $\hat{\mathbf{S}}$ with true sources $\mathbf{S}$;

2) the average correlation of the estimated mixing profiles $\hat{\mathbf{A}}$ with the ground truth $\mathbf{A}$;

3) the mean square error of the estimated $\mathbf{A}_1$-$\mathbf{A}_2$ correlation compared to the truth.

For each metric, we compared the three algorithms in two aspects, *i.e.*, under different noise conditions and at different source indices.

Simulation Results

Figure S2 illustrated the simulation results for three evaluation metrics on the whole, displayed in 3 rows. For each metric, we compared 3 algorithms in different noisy conditions (PSNRs, left column) and for diverse source distributions (source index, right column). Under each noise condition (PSNR), we illustrated the averaged estimation accuracy on sources, mixing profiles and the modal linkage respectively in Fig S2 (a), (c) and (e). It was evident that mCCA+jICA was quite robust to noise, and its BSS performance was consistently the best in all noise conditions. Consequently, joint ICA was the second best in source estimation and mCCA was the second best in mixing profile estimation; mCCA+jICA also overperformed mCCA on estimation of modal connection and their estimation errors were not influenced much by the noise. Note that when PSNR=-1dB, *i.e.*, noise was bigger than signal, all three methods can still have the estimation accuracy of $\hat{\mathbf{S}} / \hat{\mathbf{A}}$ higher than 0.55.

For each specific joint source, we plotted the mean correlation and its standard derivation across all noisy conditions via bars in Figure S2 (b) and (d). In (f), the true $\mathbf{A}_1$-$\mathbf{A}_2$ correlation was given via a yellow bar for every source, while the mean square error and its standard derivation of the link estimation were plotted in red for mCCA and in green for mCCA+jICA. Note that both very high (0.99) and low (0.07) correlation values existed in modal connection, representing both shared and distinct parts of two features. Some sources had very close (5 and 6, r =0.20, 0.23) or the same (3 and 8, r=0.36) low correlation values, which was quite ordinary in real applications of brain data fusion.

We next focused on one noisy case (PSNR=6dB) in order to dedicatedly investigate the joint BSS performance and provide a direct view of all estimated results in Figure S1, where true sources and true modal connection were also given in the left. Joint ICA separated almost all sources accurately especially for source 1,4,7 since their $\mathbf{A}_1$-$\mathbf{A}_2$ correlation >0.6, but failed to decompose the 3rd source for feature 2 whose $\mathbf{A}_1$-$\mathbf{A}_2$ correlation was lower(r=0.36). Multi-set CCA can track the modal connection more precisely than jICA, whereas it cannot completely decompose image sources in feature 1, particularly source 3-6. The proposed mCCA+jICA combined advantages of both methods and improved the performance substantially. It succeeded in separating sources and linking them correctly in a less-constrained condition, where there was no stringent requirement for the $\mathbf{A}_1$-$\mathbf{A}_2$ correlation.

Discussion

A major strength of the proposed model is that it improves the decomposition performance BSS substantially and alleviates many limitations by taking maximum advantage of the flexibilities offered by the two approaches, mCCA and jICA. Specifically, as illustrated in Figure S1 and S2, sources 1, 4 and 7 have higher $\mathbf{A}_1$-$\mathbf{A}_2$ correlation values, thus joint ICA works well, in accordance with our hypothesis. Consequently, the performance of mCCA suffers from ambiguity and misinterpretation in sources 3&8, 5&6 due to the requirement of sufficiently distinct canonical correlations; by contrast, the proposed model mitigates the performance deficits of mCCA by using a further ICA decomposition. It thus succeeds in separating sources accurately and linking them correctly for all noisy conditions and all sources, with no stringent requirement for the $\mathbf{A}_1$-$\mathbf{A}_2$ correlation.

In addition, mCCA+jICA has more reliable and higher (or equivalent) estimation accuracy on modal connection than mCCA, see Figure S1 (e) and (f), especially for sources with lower $\mathbf{A}_1$-$\mathbf{A}_2$ correlations (sources 2, 3 and 6), which could be the practical cases in brain imaging data fusion. Finally, compared to other methods, the mCCA+jICA approach does not increase the computational load appreciably; however it achieves the best performance under very flexible conditions.

References

Thomos N, Boulgouris NV, Strintzis MG. 2006. Optimized Transmission of JPEG2000 Streams Over Wireless Channels. IEEE Trans Image Process 15(1).

Figures

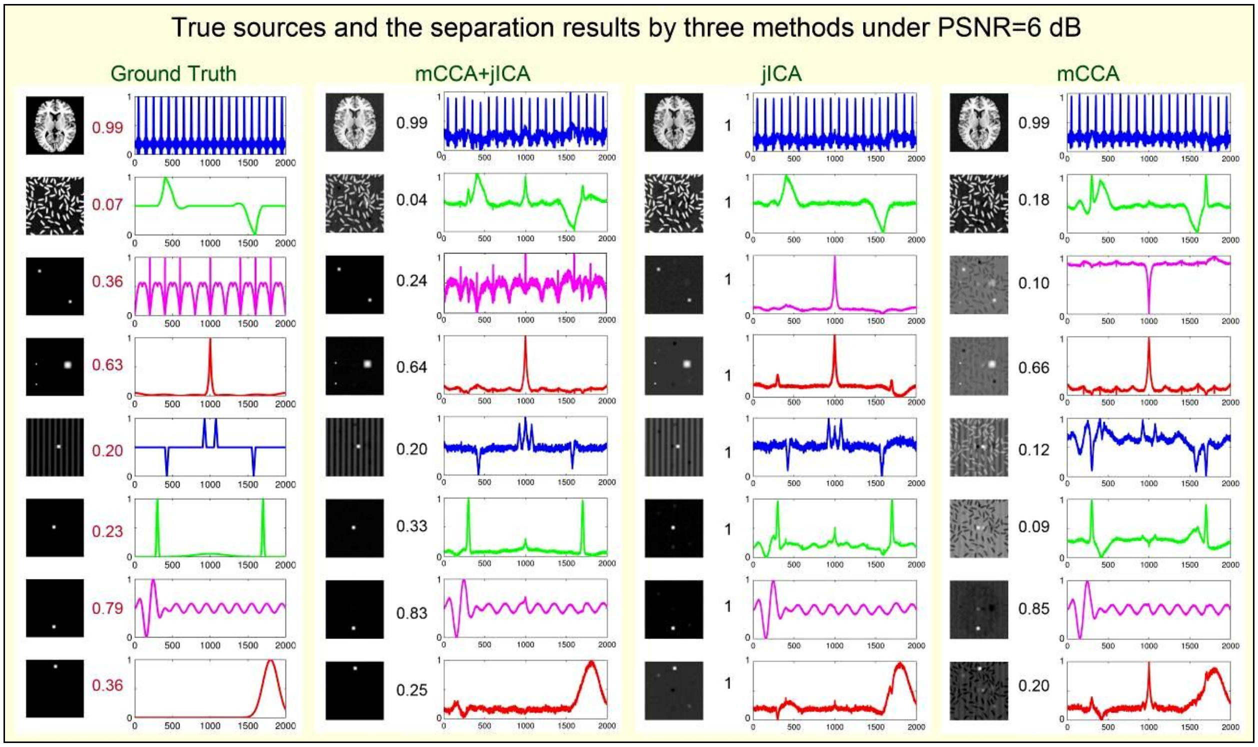

Figure S1. Simulation results of comparing separation performance of 3 methods

8 sources for each simulated modality: images (left) and one-dimensional signals (right);100 mixtures are generated for each PSNR, here we display PSNR=6dB. The correlations of mixing coefficients between corresponding sources of each modality are listed in the middle, so do their estimations. See jICA separate sources accurately except the 3rd one-dimensional signal, while mCCA estimates the modal connection accurately except that it can not decompose images quite well. mCCA+jICA combine both advantages and improve the performance remarkably.

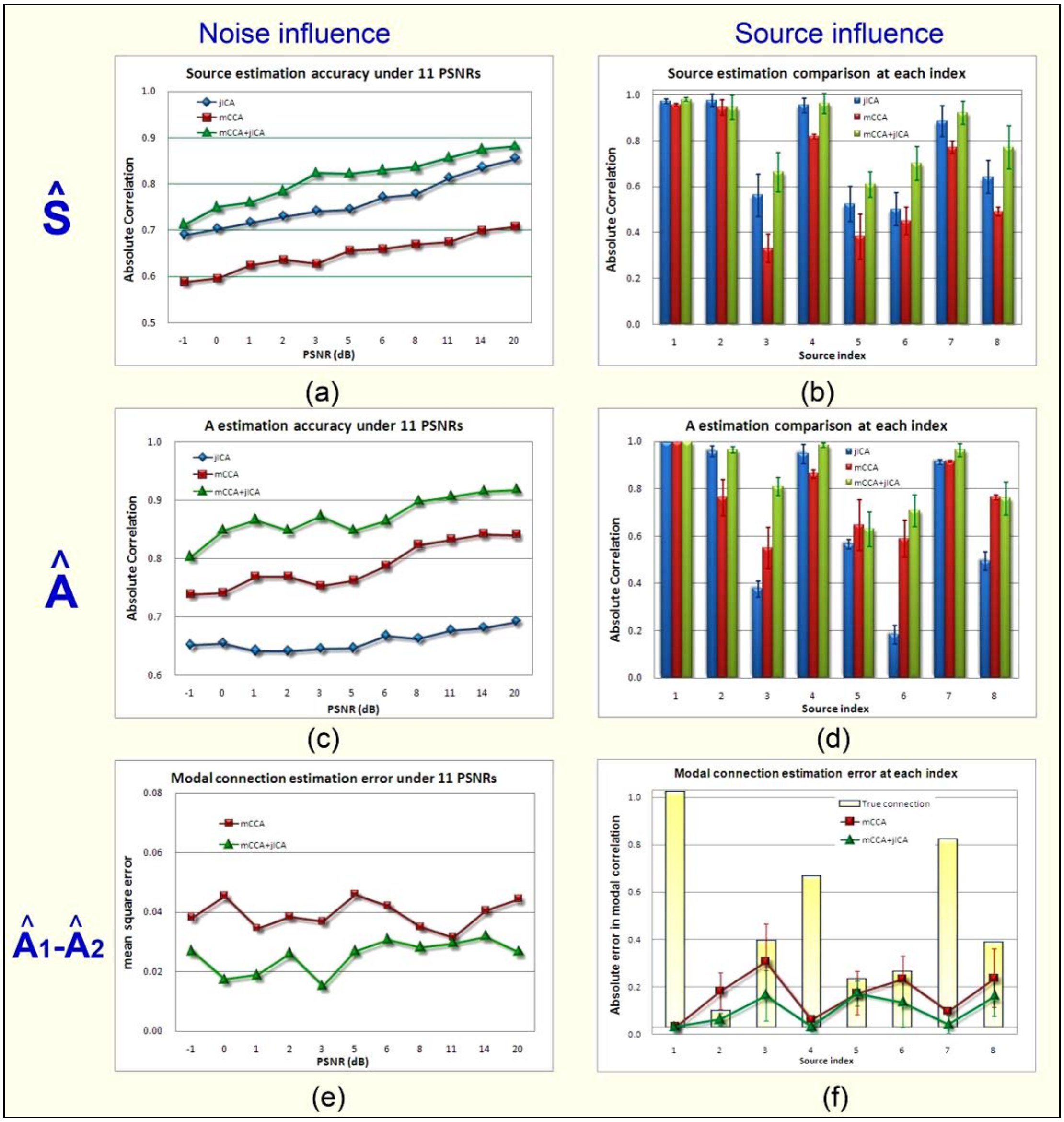

Figure S2 illustrates the whole simulation results for 3 factors and in 2 aspects. The 3 factors are source estimation ($\hat{\mathbf{S}}$), mixing matrix estimation ($\hat{\mathbf{A}}$) and modal linkage shown by correlation between mixing coefficients of each modality($corr(\mathbf{A}_1(:,i),\mathbf{A}_2(:,i))$), which are displayed in three rows. For each factor, we compared 3 algorithms in different noise conditions (left column) and for each source index (right column). Under each noise condition (PSNR), we illustrate the average of all sources' estimation. For each specific source, we plotted mean estimation and standard derivation across all noisy conditions. As portrayed, mCCA+jICA is robust for noise and source type and its source decomposition performance performs the best.