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PROJECT REPORT

AOARD Project Grant No. FA2386-17-1-0006, Proposal 16IOA006

Title: Spatiotemporal imaging exploiting structural sparsity

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1. Assigned tasks

1.1 Create simulation data

To study the roles of independency, sparseness and separation factors of functional brain networks in terms of the success of the ICA and MCA methods for blind source separation, a simulation study based on two artificial networks of rectangular shapes is conducted.

The two networks, V_1 and V_2 , are characterized by their spatial distributions and time series. A spatial distribution of each network has a dimension of 100×100 , which consists of an activation region in a blurred-edge rectangular shape, and a uniform background. Their corresponding time series are taken from those of real brain datasets.

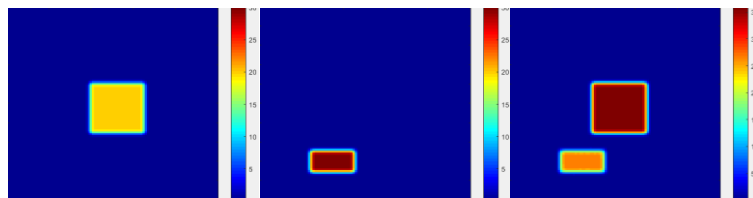


Figure 1: From left to right, networks V_1 , V_2 and their data mixture.

The two networks were mixed together and added a Gaussian noise, resulting in a mixture, which was later unmixed by the ICA and MCA methods to evaluate the performance of the algorithms.

To quantify the mathematical and spatial relationship of V_1 and V_2 , we define three parameters: independence score (denoted as I), overlapping score (denoted as $OvlScr$), and sparsity score (denoted as $SprsScr$) as

$$IndScr = V_{12}/V_1 - V_2/V,$$

$$OvlScr = V_{12}/V,$$

$$SprsScr = \frac{V_1}{V} * 100.$$

1.2 Conduct simulations and experiments evaluating performance of ICA and MCA algorithms on simulation data

The performance of the ICA and MCA methods were evaluated on simulation cases of various levels of independency, sparseness and separation factors. The parameter defining the number of trained atoms is set to 2, 3, and 4.

For the MCA method, the sparsity parameter L is set to 1, 2, 3 and 4. The initial guesses of the MCA method is taken either from data elements, mixing matrix A (taken from the ICA decompositions), or matrix U (taken from the singular value decomposition).

Simulation study are done in two scenarios: rectangular networks and realistic networks. Performance of the methods, as well as their associated effects are investigated.

2. Performed experiments

2.1 Simulation study on rectangular networks

Ten case studies were conducted on rectangular networks of varying degree of independency, sparseness and separation factors.

Experimental configurations are as follows:

- Number of trained atoms K : 2
- Sparsity parameter L : 1, 2
- MCA initialization method: data elements

2.2 Miscellaneous experiments

An experiment was done to determine the optimized value of the number of iterations for the MCA method, which was 50. Increasing it to more than 50 does not improve the convergence of the algorithm.

3. Achieved results

We found that if individual networks are independent, the ICA and the MCA methods succeed in decomposing the original networks, as shown in Fig. 2.

The performance of the MCA method depends largely on choice of its initialization method. Experiments show that data elements is not the best option for MCA initialization method. Figure 3 shows that the MCA method fails to decompose original network and there is sign of signal leakage.

The ICA method fails to decompose original network in some cases that individual networks are not independent. The decomposition result shows sign of leakage, as shown in Fig. 4. However, in some experiments that networks are not independent and not too large, both methods can decompose original networks with some leakages in them, as shown in Fig. 5.

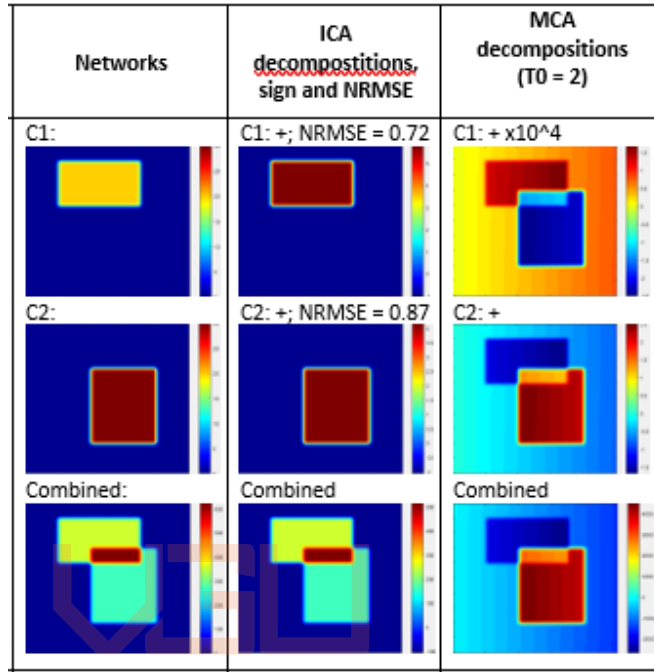


Figure 2: Simulation case 1, ICA vs. MCA decomposition results.

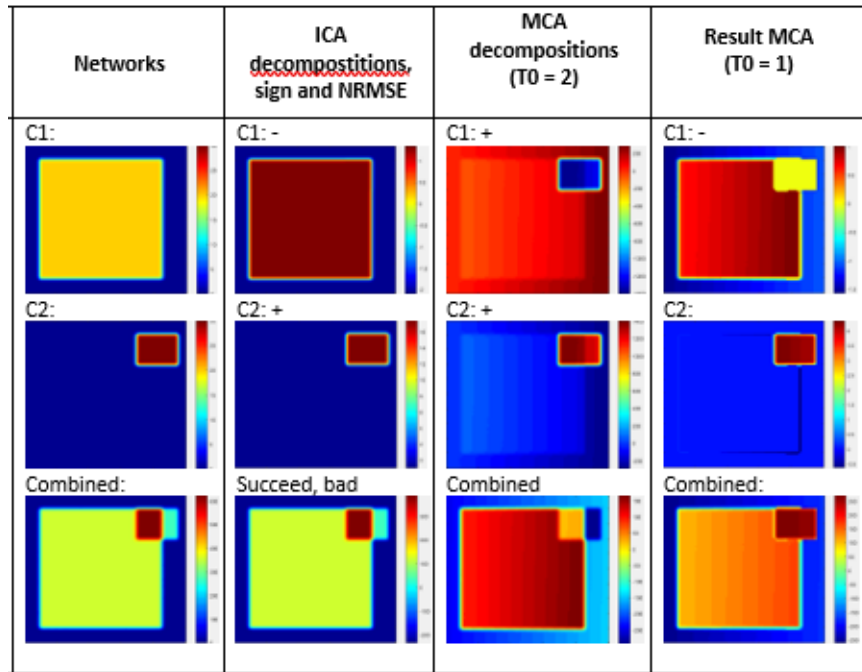


Figure 3: Simulation case 2, ICA vs. MCA decomposition results.

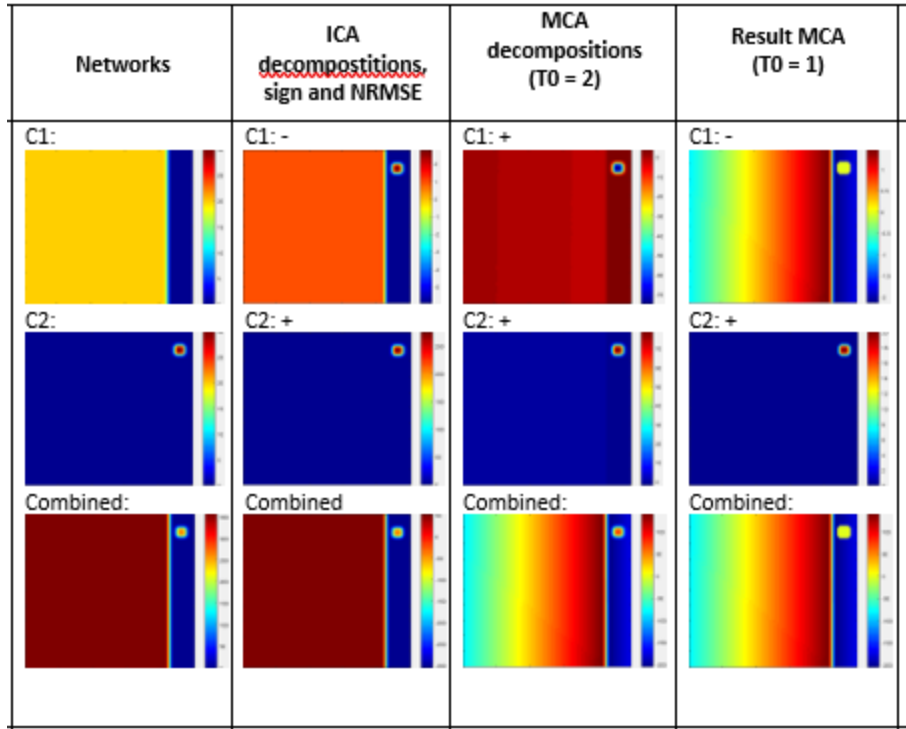


Figure 4: Simulation case 3, ICA vs. MCA decomposition results.

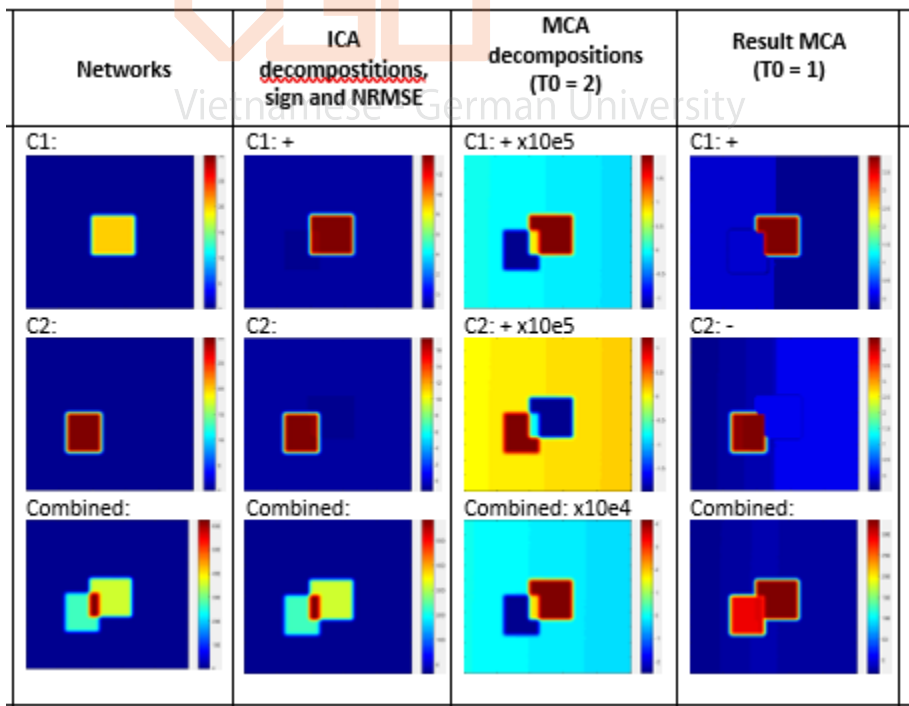


Figure 5: Simulation case 4, ICA vs. MCA decomposition results.

4. On-going tasks to be completed by the end of RA work contract

- Repeat Experiment 2.1 for realistic functional MRI network dataset, which contains 31 brain slices.
- Repeat all experiments with $K = 3,4,5, L = 3$.
- For the MCA method, repeat the experiments with initialization methods that use SVD matrix U and mixing matrix A .
- Find more simulation cases which the ICA method fails to decompose properly. The simulation networks should be as realistic as possible. In those cases, validate if the MCA method outperforms the ICA method.
- Perform the group MCA method on the newly obtained datasets.
- Prepare the journal draft with corresponding results.



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