Large-scale optimization for component analysis of fMRI resting brain data

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The use of component analysis on fMRI data is an important neuroimaging computational tool. In this paper we focus on the particular application of extracting the so-called default mode neuronal network from resting brain data ([**?**] and references therein). While independent component analysis (ICA) is currently the method of choice in this application, we investigate the advantages and limitations of using sparse PCA as an alternative to ICA. Indeed, the searched neuronal networks are mostly intrinsically very sparse and it has been suggested that ICA is a prior for sparsity rather than for statistical independence in neuroimaging [**?**].

1 Methods

We denote by $\mathbf{X}_{(m,T)}$ the fMRI signal, with m the number of voxels and T the number of time samples. Dimensionality reduction of the initial data can be expressed by :

$$\mathbf{Y}_{(n,T)} = \mathbf{W}_{(n,m)}\mathbf{X}_{(m,T)} \tag{1}$$

where $\mathbf{Y}_{(n,T)}$ is the new representation of the dataset in a n-dimensional space with $n \leq m$ since we want to reduce the dimensions of the data, and $\mathbf{W}_{(n,m)}$ is the matrix that expresses the base switch from the m to n-dimensional space.

In order to implement the ICA approach we used the fastICA algorithm which aims to achieve statistical independence between the components of $\mathbf{Y}_{(n,T)}$. On the other hand, sPCA aims to induce sparsity in the principal components contained in $\mathbf{W}_{(n,m)}$ (See [**?**] for more details) and we used the generalized power method [**?**] to implement sPCA. The optimization problem to extract one sparse principal component can be written :

$$\phi_{l_i}(\gamma) = \max_{w \in B^m} \sqrt{w^T \mathbf{C}_x w} - \gamma ||w||_i \tag{2}$$

where w is a column of $\mathbf{W}_{(n,m)}$, $\mathbf{C}_x$ is the sample covariance matrix of the data matrix, l_i indicates that the norm-i of w is used ($i = 0$ or 1), B^m is the unit ball and γ is the *sparsity-controlling* parameter.

When applied to simulated fMRI data our results suggest that sPCA gives better results than ICA when the sparsity of the networks composing the simulated data is higher than a certain threshold. However, this advantage is lost in real data because it appears that sPCA is less robust than ICA to some perturbations that exist in real fMRI data such as the motion of the patient during acquisition of the data. We then use real fMRI data from nine control patients and we design three different experiments. Those experiments aim to evaluate the ability of both techniques to extract neuronal information out of the fMRI signal.

2 Experimental results

In each experiment ICA gives better results than sPCA. We can retain two important drawbacks of sPCA compared to ICA. First, the neuronal networks extracted through sPCA appear to be more affected by perturbations such as motion of patients, making the extraction of neuronal components from one subject to another less robust than with ICA. Second, sPCA does not seem to be able to isolate neuronal information in a few components only, whereas ICA does.

3 Ongoing work

In addition to sparsity, neuronal networks are also highly structured. We currently investigate an optimization problem of the form :

$$\phi(\gamma) = \min_{w \in B^m} f(w) + \gamma\Omega(w) \tag{3}$$

as presented in [**?**] in which the regularization term $\Omega(w)$ induces sparsity *and* structure in w.

References

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