Blind Separation of Sources in functional MRI sequences

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ABSTRACT

Functional Magnetic Resonance Imaging (fMRI) is an important and popular tool for studying the human brain activity. In most fMRI scans, the BOLD technique is used, producing an image of the blood oxygenation level throughout the brain. High oxygenation levels represent high activity of brain regions responsible for performance of a specific task.

The process can be modeled as a linear mixture of independent localized sources of oxygenation, where no apriori information is known about their properties.

A problem of separating such sources is referred to as "Blind Source Separation" (BSS) and there exist powerful tools to solve it.

The project focuses on separating brain activity sources from a sequence of fMRI images using BSS methods and the approach of sparse representations.

THE PROBLEM

The images produced by fMRI scans contain mixtures of localized sources of oxygenation, where no apriori information is known about their properties.

In addition, the images are affected by noise and other artifacts, resulting from head motion, brain background activity, the scanners themselves etc.

The mixing process can be modeled as a linear mixture of independent sources, and thus restoring the separate sources from the fMRI scan can be considered as a “Blind Source Separation” (BSS) problem.

Our goal is to separate the different oxygenation sources from the fMRI scan images, using BSS methods.

\[ \mathbf{m} = \mathbf{A} \cdot \mathbf{s} \]

\[ \hat{\mathbf{s}} = \mathbf{A}^{-1} \cdot \mathbf{m} \]
THE SOLUTION

The solution consists of 2 stages –
1) Image preprocessing and sparse representation.
2) Implementing blind source separation methods.

The preprocessing stage included spatial smoothing of the images, identifying and removing the image “background” (static brain image, not including the task related activity), and sparse representation of the image using the Wavelet Packet transform. Principal Component Analysis (PCA) was later introduced for the dimension reduction of the problem.

For solving BSS problems, there exist several methods, out of which we have implemented two:

a. Geometric mixing matrix estimation, using:
   • Angular histogram: Finding the most likely angle of the sources (represented as vectors), and reconstructing the mixing matrix from this angle.
   • Projection to hyper-sphere and clustering: Projecting and clustering the sources on half a sphere, identifying the clusters’ centers of mass and reconstructing the mixing matrix according to the angles of these centers.

b. ICA - Infomax:
   Independent Component Analysis (ICA) is a statistical technique for decomposing a dataset into independent subsets. Infomax is one of the ICA methods, which is based on maximizing the output entropy of a neural network with non-linear outputs.

TOOLS

The Project was programmed in Matlab 6, on a PC platform.
The main Matlab tools used were the Wavelet toolbox, image processing, clustering and PCA tools.
The ICA toolbox, developed by Scott Makeig of the Salk Institute, was used to implement Infomax separation.

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