HIERARCHICAL TEMPORAL BLIND SOURCE SEPARATION OF fMRI DATA

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TEMPORAL BLIND SOURCE SEPARATION

Temporal Blind Source Separation (BSS) aims at revealing interesting timecourses in the fMRI data. Since the number of timecourses in an fMRI data set is very large while the number of timepoints in each timecourse is far fewer, this is an ill-posed problem. A commonly applied remedy is to apply a Principal Component Analysis (PCA) pre-processing step in order to obtain a manageable samples to timecourses ratio.

WHY PCA MAY FAIL

When applying PCA one implicitly assumes that interesting signals have high variance. This assumption may not be valid in an fMRI context where for example the BOLD response can be weak. Another reason for failure is that it may be possible to find a combination of the very large number of irrelevant noise timecourses that attain high variability by pure coincidence.

EXAMPLE

This example demonstrates a simulated situation where PCA pre-processing fails. Three differently shaped timecourses of length 200 samples were inserted in small patches embedded in Gaussian noise, see Fig. 1a. Fig. 1c shows the (unsuccessful) result of a BSS method where PCA was used as pre-processing. The failure is due to the small support area of the "interesting" timecourses compared to the large number of noise timecourses. In Fig. 1b, the result of the proposed hierarchical approach is shown.

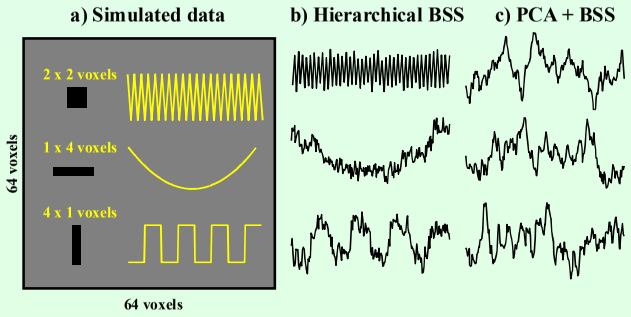

Figure 1. *Artificial timecourses embedded in Gaussian noise in regions of 4 voxels and the result when applying two different BSS approaches.*

HIERARCHICAL DIMENSIONALITY REDUCTION

In traditional temporal exploration of fMRI data, the fact that we have knowledge about the "sensor array", i.e. the spatial context the timecourses exist in, is ignored. The proposed method exploits the spatial relations in a hierarchical manner to reduce the dimensionality of the data to a manageable size. This is achieved by *repeated* application of your favourite BSS method. First, divide the fMRI images into 2x2 patches and apply BSS on the four timecourses in each patch (which is possible without dimensionality reduction). Next, concatenate the 2x2 patches into 4x4 patches and propagate the most interesting timecourses from the underlying 2x2 patches to the 4x4 patch above. Then apply BSS on each 4x4 patch and repeat the above steps, see Fig. 2. The approach is similar to a tournament where winning timecourses in the BSS qualify for further processing while uninteresting timecourses are discarded. The procedure can also be seen as a hierarchy where dimensionality reduction is achieved between each level. PCA can therefore be avoided. For example, the inserted timecourses in the previous example will be propagated through the hierarchy and not drowned in the noise timecourses.

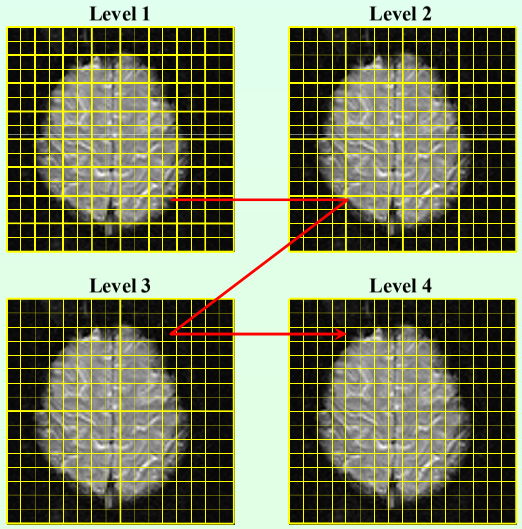

Figure 2. *Hierarchical processing*

REAL DATA EXAMPLE

In fMRI data, slowly varying drifts of global nature, i.e. with large spatial support, are abundant. The first timecourses resulting from both the PCA based and the hierarchy based methods are of this kind. PCA is well suited for finding such signals as it operates on the entire data set simultaneously. Consequently, somewhat "cleaner" timecourses are produced by PCA, see the first components in Fig. 3. After the global signals, the results from the two different approaches begin to deviate, see last components in Fig. 3, and the advantages of the hierarchical approach can be seen. Figure 4 shows the number of interesting signals detected in each patch by the hierarchical method at different levels in the hierarchy.

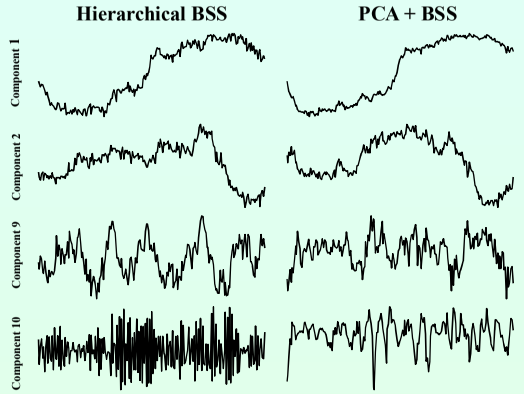

Figure 3. *The resulting temporal components when using a real fMRI data set.*

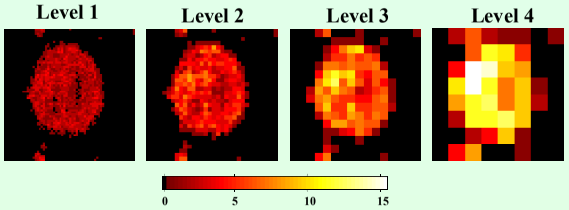

Figure 4. *The number of interesting components propagated in the hierarchy.*

CONCLUSIONS

For detecting global drifts, dimensionality can be robustly reduced by PCA. For finer details, the hierarchical approach has potential to reveal additional information.