A Data-Driven fMRI Analysis using K-SVD Sparse Dictionary Learning

K. Lee[1], and J. Ye[1]

[1]Dept. Bio & Brain Engineering, KAIST, Daejon, Korea, Republic of

Introduction: Statistical parametric mapping (SPM) is widely used for the statistical analysis of brain activity with fMRI. However, if the general linear model employs a fixed form of a canonical HRF, the ignorance of experimental and individual variance can lead to inaccurate detection of the real activation area. A variety of data-driven methods, which combine independent component analysis (ICA) with statistical analysis of fMRI dataset, were suggested to overcome the problem, such as the `HYBICA' approach [1] and the unified `SPM-ICA' method [2]. However, recent study demonstrates that representation of the brain fMRI using sparse components is more promising rather than independent components [3]. Also, the real brain fMRI signal may be regarded as a combination of small set of dynamic components, where each of them has different signal patterns and sparsely distributed in each voxel. Hence, we employ the K-SVD [4], a powerful sparse dictionary learning algorithm, to decompose the neural signal into dictionary atoms with specific local responses. Using the trained sparse dictionary as a design matrix in SPM, we extract which signal components contribute to the neural activation. We show the proposed method adapts the individual variation and extract the activation better than conventional methods.

Theory: The general linear model (GLM) model explains the response variable in terms of a linear combination of the explanatory variables plus a residual error term as:

$$Y_j = d_{j1}x_1 + \cdots + d_{ji}x_i + \cdots + d_{jN}x_N + \varepsilon_j \ , \quad (1)$$

where Y_j denotes the each observations $j = 1,\dots,J$, a set of $N(N < J)$ sparsely distributed explanatory variables are denoted by d_{ji}, and x_i at $i = 1,\dots,N$ are unknown parameters corresponding to each explanatory variables d_{ji}. We assume that the measurement is a linear combination of small set of dynamic signals that have distinct synchronous temporal patterns, which are originated from activated visual, auditory, motor area and etc, due to the complex brain connectivity. In this model, each voxel has sparse contribution from the signals which are localized in a small set of region. In our model, we assume $D = \{d_j\}_{j=1}^{K}$ are unknown. To extract the unknown explanatory variables d_{ji}, we employed K-SVD algorithm [4], which is a powerful iterative algorithm for training sparse dictionaries. Here, given a set of training signals $Y = \{y_i\}_{i=1}^{N}$, we search the best possible dictionary $D = \{d_j\}_{j=1}^{K}$ for the sparse representation of the measurement *Y* as:

$$min_{D,X}\{\| Y - DX \|_F^2\}, \qquad subject\ to \quad \forall i, \| x_i \|_0 \le T_0 \ , \quad (2)$$

where T_0 is a fixed and predetermined number of nonzero entries and x_i denotes the *i-th* column of *X*. The K-SVD algorithm applies two steps per each iteration. In sparse coding stage, we find the best coefficient matrix *X* for a given dictionary *D* as:

$$min_{x_i}\{\| y_i - Dx_i \|_2^2\}, \qquad subject\ to \quad \forall i, \| x_i \|_0 \le T_0 \ , \quad (3)$$

which can be solved using orthogonal matching pursuit (OMP) and etc. Then, in the dictionary updating stage, we change the columns of *D* sequentially for given $\{x_i\}_{i=1}^{N}$. We denote E_k as the residual for all the *N* examples when the contribution from the *k-th* atom is eliminated. Then we select the error columns that correspond to $E_k^R = E_k \Omega_k$, where Ω_k is defined as an $N \times |w_i|$ matrix with ones on the $(w_k(i), i)$-*th* entries, and zeros elsewhere, where w_k is defined as: $w_k = \{i | 1 \le i \le K, x_T^k(i) \ne 0\}$. Then, Eq. (2) is rewritten as minimizing $\| E_k^R - d_k x_T^k \|_F^2$. For this, we take singular value decomposition of E_k^R, and determine d_k and x_T^k using the best rank-1 approximation. This is repeated until convergence. Finally, the resultant trained dictionary atom d_k is used to the design matrix in GLM model.

Experiments: The proposed method was applied to a right finger tapping task with block paradigm to evaluate the performance. A *15* sec task period alternated with a *72* sec resting period was repeated *4* times for each subject followed by an additional *30* sec of rest. The total recording time was *480* sec. A total of *3* healthy right-handed subjects were examined (*mean age=25±2*). A *3.0T* fMRI system (ISOL, Republic of Korea) was used to measure the BOLD response. During every experiments, the EPI sequence was used with TR/TE=*3000/35 ms*, flip angle=*80°*, *35* slices, *4 mm* slice thinkness.

Data analysis: The data were spatially realigned to correct the changes in signal intensity over time which can arise from within-subject head motion. Spatial registration and normalization were applied. We only extracted the voxels corresponding to the brain region from the 3-dimensional BOLD response measured with fMRI. Then the data was down-sampled at spatial direction to decrease the computation time in K-SVD learning. We used a discrete cosine transform basis set with cutoff frequency of *1/128 Hz* to eliminate unknown global trends, and temporal smoothing using *1.5* sec full-with at half maximum of the Gaussian smoothing kernel. Then, we employed K-SVD to the pre-processed fMRI finger tapping data. The number of dictionary elements was *50* for subject 1 and subject 2, and *53* for subject 3. Maximum coefficients to be used in OMP coefficient calculations was set to *5*, and *15* iterations were performed for each data. According to the algorithm, the dictionary matrix *D* was trained and entered to the design matrix. The general linear model is then applied to statistically analyze the measured BOLD signal. The restricted maximum likelihood estimation of the parameters and inference with F-statistics are then conducted using the SPM package.

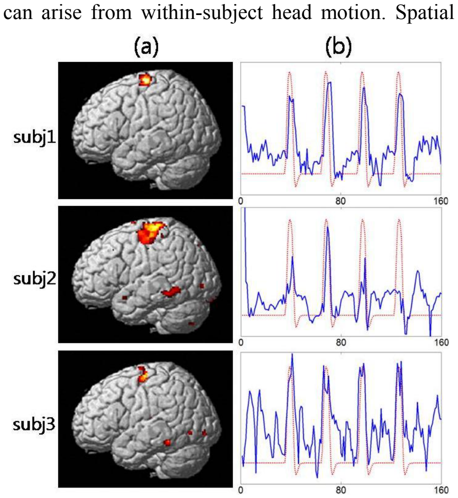

Figure 1. (a) Activation maps of three subjects' fMRI data using design matrices constructed using trained dictionaries by K-SVD shown in (b). Red line corresponds to the canonical HRF convolved with experimental paradigm, and the blue line corresponds to the individual HRF extracted using K-SVD

Results: We have shown the activation map using trained dictionary by K-SVD. For three subjects, the activation maps with $p < 0.05$ tightly localized on the left primary motor cortex (see Fig 1.(a)). The proposed method adapts the individual variation as can be seen in the estimated dictionary in Fig 1.(b).

Conclusions: In this paper, we proposed the sparse dictionary learning for SPM, which decomposes the activation signals into sparse signal atoms. The employment of K-SVD in GLM constructs the data-driven model for the brain fMRI analysis. The data-driven design matrix containing the time course of the trained dictionary is individually adaptive and extracts the activation better than conventional methods.

References: [1] M.J.McKeown, NeuroImage, vol. 11, no. 1, pp. 24-35, 2000,
[2] D.Hu et al., Neuroimage, vol. 25, no. 3, pp. 746-755, 2005, [3] I. Daubechies et al., PNAS, vol. 106, no. 26, pp. 10415, 2009,
[4] M.Aharon et al. IEEE Tr. Sig. Pro., vol. 54, no. 11, pp. 4311, 2006