

# Compressed sensing fMRI using optimized temporal basis

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**Introduction:** Functional MRI (fMRI) has become popular with the developments of echo planar imaging (EPI) sequences. However, EPI needs more image quality improvements for some applications. For example, EPI images suffer from field inhomogeneity artifacts resulting from signal losses in some areas especially around air-tissue interfaces. These artifacts can be minimized with, for example, thin slice thickness [1]. This strategy, however, requires more acquisition time so that temporal resolution or field of view should be sacrificed. In this paper, to address this problem, we applied a compressed sensing dynamic MR imaging algorithm called k-t FOCUSS [2] to fMRI. To resolve degradation of SNR at accelerated acquisition, more number of repetitions of tasks were conducted. Then, from down-sampled k-space data, we obtained accurate brain activation maps for right finger tapping experiments. We verified the reliability of our results by plotting receiver operating characteristic (ROC) [3] curve.

**Theory:** According to compressed sensing theory [4], very accurate signal reconstruction is possible even from very limited number of measurements by solving  $l_1$  minimization if the signal can be sparsely represented. The k-t FOCUSS algorithm achieves  $l_1$  minimization solution for sparse signal  $\rho$  by iteratively solving the following equation:

$$\rho_{n+1} = \Theta_n S^H F^H (FS\Theta_n S^H F^H + \lambda I)^{-1} \nu, \quad (1)$$

where  $\nu$  and  $F$  represent randomly down-sampled measurements on k-t space and corresponding down-sampled Fourier transform, respectively, and  $\Theta_n = W_n W_n^H$ . Here,  $W_n$  is a diagonal matrix which is iteratively updated as  $W_n = \text{diag}(|\rho_n|^{0.5})$ , and  $S$  implies a sparsifying transform. In cardiac cine imaging, hearts have periodic motions, so simple Fourier transform along temporal direction can be used for  $S$  [4]. However, when an object has irregular motions such as in fMRI, more general sparsifying transform should be considered for better sparse representation. Karhunen-Loeve transform (KLT) or principal component analysis (PCA) is used in temporal direction in this paper. Unlike the Fourier transform, KLT is a data dependent transform. In our approach, the eigenvectors of the covariance matrix of temporal measurements at fully sampled low-frequency area are used as the KLT bases.

**Methods:** To evaluate the performance of k-t FOCUSS for fMRI, we designed an event related paradigm of right finger tapping (RFT) experiments as shown in Fig. 1. During the task, k-space data were acquired on 64 x 64 matrix size and 35 slices with an EPI sequence at a 3.0 T MRI (ISOL technology of Korea) scanner. To simulate the accelerated fMRI, the number of phase encodings was reduced by 4-fold while keeping the number of task blocks with 40. To evaluate the performance improvements of k-t FOCUSS using KLT, a different version of k-t FOCUSS, which uses Fourier transform (FT) was used to reconstruct fMRI from same measurements. As conventional methods, direct Fourier inversion of same number of low-frequency k-t space data as well as the sliding window (SW) was also implemented. To assess the performance of 4-fold accelerated fMRI, we used the control data sets that are composed of fully sampled data sets but the number of task repetitions was reduced to 10. Note that even if the number of measurements is same between accelerated fMRI and the control experiments, only in the case of the accelerated fMRI, TR can be reduced by skipping phase encoding steps in real implementation. Then, using the group analysis of SPM (statistical parametric mapping) tool box on Matlab, activation maps were obtained from 12 subjects. For quantitative evaluation, ROC curves were also calculated. ROC curves plot a true-positive fraction (TPF) versus a false-positive fraction (FPF). Applying ROC curves to fMRI, TPF implies the ratio of the number of detected voxels as activated among truly activated voxels to the total number of truly activated brain voxels; and FPF indicates the ratio of the number of detected voxels to the total number of truly non-activated brain voxels. In order to draw a ROC curve, the ground truth for the activated area should be determined in advance. In this paper, we simply choose the results of fully sampled data during 40 repetitions as a ground truth since the goal of experiments is to identify the feasibility of accelerated fMRI.

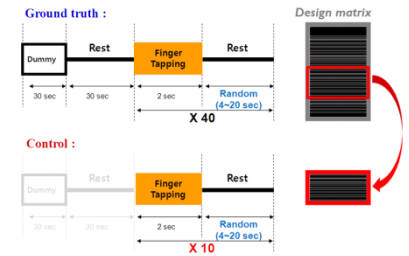


Fig. 1. Event related fMRI paradigm for RFT

**Results:** Fig. 2 (a) illustrates the activated maps and ROC curves for different methods. Only the results of k-t FOCUSS using KLT show the similar activated maps to the ground truth. ROC curves quantitatively compare the accuracy of activation maps. The result of k-t FOCUSS using KLT plots the best ROC curve even better than the control experiments as shown in Fig. 2 (b).

**Conclusions:** We have confirmed that compressed sensing based accelerated fMRI using KLT bases shows very accurate results using ROC curve analysis.

## References:

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- [3] Sorenson et al. MRM, vol. 36, pp. 737-744, 1996
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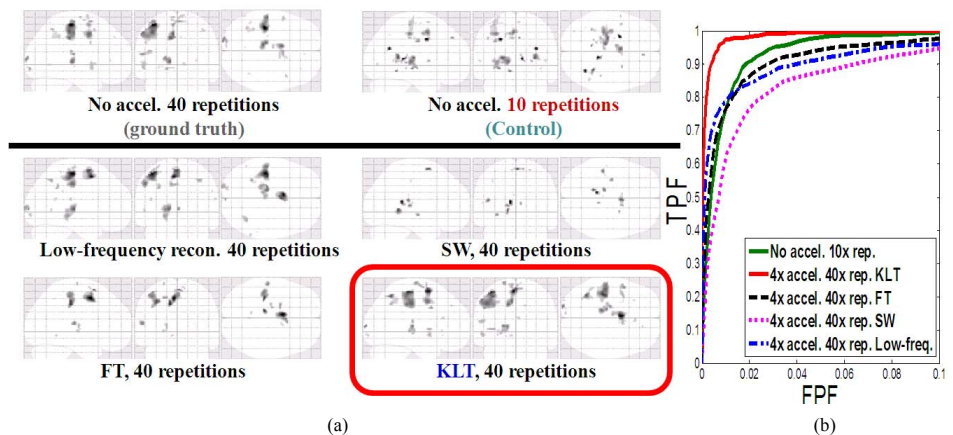


Fig. 2. Activation maps and ROC curves.