PERFORMANCE EVALUATION OF ACCELERATED FUNCTIONAL MRI ACQUISITION USING COMPRESSED SENSING

Hong Jung, Jong Chul Ye

Bio-Imaging & Signal Processing Lab., Dept. of Bio and Brain engineering
Korea Adv. Inst. of Science & Technology (KAIST)
373-1 Guseong-dong Yuseong-gu, Daejon 305-701, Republic of Korea

ABSTRACT

Functional MRI (fMRI) has been widely accepted as a standard tool to study the function of brain. However, because of the limited temporal resolution of MR scanning, researchers have experienced difficulties in various event related cognitive studies which usually require higher temporal resolution than the current acquisition protocol. Even if several accelerated fMRI methods have been proposed to overcome the limited temporal resolution, the results have not been widely accepted since there were concerns whether the result came from blood oxygen level-dependent (BOLD) signal or artifacts due to down sampling. The main contribution of this paper is to propose a new high spatio-temporal resolution fMRI technique based on compressed sensing theory and to justify the performance using receiver operating characteristic (ROC) curve.

Index Terms— fMRI, compressed sensing, FOCUSS, Karhunen-Loeve transform, ROC curve

1. INTRODUCTION

Functional MRI (fMRI) is a technique to detect activated area in the brain with respect to the given task by measuring the change of blood oxygen level-dependent (BOLD) contrast. However, since the change of BOLD signal is very small compared to full MR signal, fast scan is required to prevent noisy signal due to subject motion or tissue pulsation [1]. As MR system and fast sequencing methods like echo-planar imaging (EPI) have been developed, fMRI has been positioned as a standard tool for functional study of brain. With current technique, fMRI using EPI has spatial resolution of about $3\times3\times4$ mm^3 and temporal resolution up to 1 to 3 sec. This level of temporal resolution is fast enough for the fMRI experiments such as finger tapping or working memory study which are performed during relatively long time period. However, for various event related cognitive fMRI study whose brain activations are usually detected over the broad cortex during hundreds or a few milliseconds much higher temporal resolution is still demanded [2]. Of course, it is possible to achieve higher temporal resolution by reducing the number of slices along z-axis but in that case we can not accurately localize the activated area since the spatial resolution along z-direction becomes poor.

To resolve the temporal resolution limitation, fMRI can be combined with MEG or EEG that has high temporal resolution [2]. However, there still remain problems to align MEG or EEG signal of low spatial resolution onto high spatial resolution MR images.

As an effort to develop fMRI as a stand alone tool for functional brain analysis, parallel imaging such as SENSE is used for accelerated fMRI in [1, 3]. When the reconstructed image using SENSE from accelerated measurement is compared to fully sampled image using conventional method, no big difference is noticeable with naked eyes. However, reduced signal to noise ratio (SNR) and remaining aliasing artifacts due to reduced scan time and incomplete g-factor respectively should be carefully resolved. Furthermore, since the noise pattern becomes different as well, the detected activated area after statistical processing looks different from that of fully sampled one. Therefore, it is still controversial if parallel imaging is suitable for high temporal resolution fMRI.

As another alternative, compressed sensing [4] can be considered which is gathering huge interests in dynamic MRI area. Compressed sensing is a new sampling theory that tells us that very accurate reconstruction is possible even from very limited number of measurements under Nyquist sampling limit using sparsity of images. In [5, 6], compressed sensing is proved as a high spatio-temporal resolution technique for cardiac MRI. In cardiac MRI, the change of signals with respect to different cardiac phase is very strong enough to be clearly seen with naked eyes. However, as mentioned above, in fMRI the change of BOLD signal is very weak compared to full MR signal so that it is essential to analyze and assess statistical characteristic of reconstructed images before claiming the effectiveness of compressed sensing.

The main contribution of this paper is to apply compressed sensing based algorithm called k-t FOCUSS [5, 6]

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to fMRI and then to justify the high spatio-temporal resolution fMRI by comparing receiver operating characteristic (ROC) curves [7] of the results of k-t FOCUSS and those of fully sampled results. ROC curve plots true-positive fraction (TPF) versus false-positive fraction (FPF) so that this can be used as a standardized and statistically meaningful method for signal-detection accuracy [7]. Therefore, when analyzing various fMRI results, ROC curve is very effectively used in determining whether the detected activated area comes from activated signal or noise signal. In this paper, block designed right finger tapping (RFT) experiments were performed. To implement accelerated fMRI, 2-fold and 4-fold down sampled data were used during 10 block repetition and then the results were reconstructed by k-t FOCUSS. As control experiments, the fully sampled results during 5 block repetition and 3 block repetition were used. Note that the total number of sampled data is comparable in both cases. If the results of accelerated fMRI is comparable to control results, it is possible to obtain very reliable high temporal resolution fMRI which is usually required in event related cognitive study.

Note that even with the compressed sensing approaches, the signal to noise ratio of the resulting reconstruction should *not* be as good as the full data cases. One of our main contribution is the idea such that high temporal resolution can be achieved through accelerated acquisition and the reduced number of measurements can be compensated by increasing the number of blocks. This is nicely fitted with general linear model (GLM) techniques that has been extensively used in statistical parameter mapping for fMRI. In GLM framework, the increase number of blocks guarantees the improved signal-to-noise ratio. Another important contribution of this paper is that Karhunen-Loeve transform (KLT) along temporal direction in k-t FOCUSS outperfoms other implementations in fMRI applications due to its adaptiveness of temporal variation. Experimental results show the results of various versions of k-t FOCUSS and compare them with control results to justify high spatio-temporal resolution fMRI through accelerated acquisition.

2. THEORY

2.1. k-t FOCUSS: compressed sensing dynamic MRI

According to compressed sensing theory [4], very accurate signal reconstruction is possible even from very limited number of measurement by solving l_1 minimization if the signal can be represented sparsely in a modeling basis and the measurement bases are incoherent from the modeling basis. Since these requirements are very easily fulfilled in dynamic MRI, we successfully applied compressed sensing to cardiac cine imaging with new algorithm called k-t FOCUSS in [5, 6]. k-t FOCUSS algorithm can be briefly summarized as follows:

$$\boldsymbol{\rho}_{l+1} = \boldsymbol{\rho}_0 + \boldsymbol{\Theta}_l \mathbf{A}^H \left(\mathbf{A}\boldsymbol{\Theta}_l\mathbf{A}^H + \lambda\mathbf{I}\right)^{-1} \left(\boldsymbol{\upsilon} - \mathbf{A}\boldsymbol{\rho}_0\right), \quad (1)$$

where $\boldsymbol{\upsilon}$, $\mathbf{A}$, and $\boldsymbol{\rho}_0$ represent down-sampled measurements on k-t space, sparsifying transform, and prediction term, respectively, and $\boldsymbol{\Theta}_l = \mathbf{W}_l\mathbf{W}_l^H$. Here, $\mathbf{W}_l$ is a diagonal matrix which is iteratively updated with the solution from the previous step:

$$\mathbf{W}_l = \begin{pmatrix} |\Delta\rho_l(1)|^p & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & |\Delta\rho_l(N)|^p \end{pmatrix}, \quad (2)$$

where N is the total number of unknown coefficients. Note that k-t FOCUSS asymptotically solves l_1 minimization problem by setting $p = 0.5$ in Eq. (2) [5].

In cardiac imaging, since heart has periodic motion, simple Fourier transform along temporal direction could be used as a sparsifying transform $\mathbf{A}$ [5] and for further improvements the prediction term $\boldsymbol{\rho}_0$ was determined by motion estimation/compensation (ME/MC) [6]. However, when the subject shows irregular motion, more general sparsifying transform should be considered rather than simple Fourier transform. In this paper, as an alternative, Karhunen-Loeve transform (KLT) is used in temporal direction for function MRI.

2.2. KLT basis

Unlike the Fourier transform, KL transform is a data dependent transform. More specifically, let $\boldsymbol{\sigma}_x$ denote a vector containing pixel intensities on x position at different time points spanning 1 to N_t. Then, the covariance matrix $\mathbf{C}_x$ of $\boldsymbol{\sigma}_x$ can be expanded as follows:

$$\mathbf{C}_x = \sum_{k=1}^{N_t} \lambda_k \boldsymbol{\psi}_k \boldsymbol{\psi}_k^H \quad (3)$$

where $\{\lambda_k\}_{k=1}^{N_t}$ and $\{\psi_k\}_{k=1}^{N_t}$ are the eigenvalues and the corresponding orthonormal eigenvectors (or principle components) of $\mathbf{C}_x$ [8]. Using Eq. (3), we can create the following expansion:

$$\boldsymbol{\sigma}_x = \sum_{k=1}^{N_t} \rho_k^x \boldsymbol{\psi}_k \ . \quad (4)$$

for some expansion coefficients $\boldsymbol{\rho}^x = \{\rho_k^x\}_{k=1}^{N_t}$. Then, the KLT bases are obtained with $\{\boldsymbol{\psi}_k\}_{k=1}^{N_t}$. It is well-known that the KLT is the optimal energy compaction transform and that most of the energy is compacted in a small number of expansion coefficients [8], which is an ideal property from the compressed sensing perspective.

Note that the principle components $\{\boldsymbol{\psi}_k\}_{k=1}^{N_t}$ in Eq. (4) are data dependent, hence they are, in fact, varying with respect to the specific x position. However, estimating autocovariance for each x position is a very underdetermined problem due to the limited number of measurements. Hence, assuming that the motion of the moving parts are about the same for all x position, we can estimate the autocovariance function using measurements from all x's. More specifically, the low resolution initial image can be easily obtained from fully sampled low frequency k-space samples. Then, the temporally varying low resolution images are used to estimate the covariance matrix $\mathbf{C}_{all}$ for all x's. Then, the principle component $\{\psi_k\}_{k=1}^{N_t}$ can be readily obtained using eigen-decomposition and $\mathbf{A}$ in Eq. (1) corresponds to $\{\psi_k\}_{k=1}^{N_t}$. It is important to note that even though principal components are obtained from low spatial resolution images, the temporal changes are not smoothed at all because we use fully sampled data along temporal direction within limited low spatial frequency k-space in order to obtain full set of principal components. Therefore, the KLT keeps any high temporal frequency information.

3. MATERIALS AND METHOD

3.1. Block paradigm: Right finger tapping experiments

To evaluate the performance of k-t FOCUSS in fMRI, we designed block paradigm of right finger tapping (RFT) experiments as shown in Fig. 1 Before starting the RFT tasks, 42

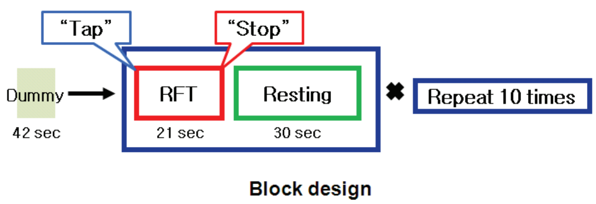


Fig. 1. The paradigm for block designed RFT experiments

sec was given to stabilize the subject and MR scanner. Then, RFT and resting were repeated ten times. The subject started tapping right finger when a 'tap' sign appears and stopped tapping when a 'stop' sign is shown. Each of RFT period was 21 sec and resting period was given after each RFT period during 30 sec. The total recording time was 552 sec.

3.2. Data acquisition

A 3.0 T MRI system manufactured by ISOL Technology of Korea was used to acquire fMRI data. During the blocked task paradigm, the echo planar imaging (EPI) was used with TR/TE=3000/35 msec and flip angle=80°. k-space data are acquired on 64 × 64 matrix size and 35 slices with 4 mm slice thickness. Each voxel size was 3.4375 × 3.4375 × 4 mm^3 and the field of view was 220 × 220 mm^2.

3.3. Down sampling experiments

For implementation of high temporal resolution fMRI, the number of phase encoding was reduced by 2-fold and 4-fold for each time frame while keeping the number of blocks with 10. According to compressed sensing, the sampling basis should be incoherent so that the random sampling pattern was employed as shown in Fig. 2. Especially, the low frequency region was fully sampled and these fully sampled data were used to obtain KLT basis. For different versions of k-t FOCUSS that are using Fourier transform along temporal direction, ME/MC, and KL transform along temporal direction, same down sampled data were used. As a conventional method, sliding window was also implemented.

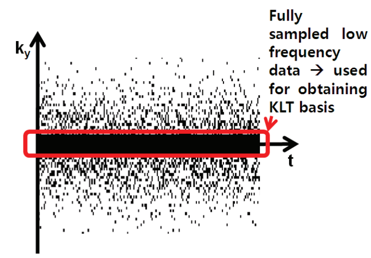


Fig. 2. The accelerated sampling pattern on k-t space

To justifiably assess the performance of 2-fold and 4-fold accelerated fMRI, we used about same number of measurements as control data sets which were composed of fully sampled data sets but the number of blocks was reduced to 5 and 3. Note that even if the number of measurements is comparable between accelerated fMRI and control experiments, only in the case of accelerated fMRI TR can be reduced by skipping phase encoding steps in real implementation.

3.4. ROC curve

ROC curve plots true-positive fraction (TPF) versus false-positive fraction (FPF). When applying ROC curve 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 as activated among truly non-activated brain voxels to the total number of truly non-activated brain voxels. Therefore, in order to draw 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 full number of blocks as a ground truth since the goal of experiments is to identify the feasibility of compressed sensing based high temporal resolution fMRI rather than identifying truly activated area during RFT tasks. On the top of Fig. 3 the ground truth is shown. The left motor cortex area is correctly detected as well known as a target area for RFT task. To calculate the activated area, the SPM (statistical parameteric mapping) toolbox was used on Matlab. The voxels whose values are over the threshold on the F-statistical map when FWE (family-wise error rate) corrected p-value $\leq$ 0.05 were classified as truly activated area.

Then, for each method TPF and FPF are calculated with respect to different threshold values on F-map. The closer to 1 the area under the ROC curve is, the better the accuracy is.

4. RESULTS

In Fig. 3, activated areas were detected for different methods using SPM toolbox. Control result, sliding window (SW), and k-t FOCUSS results using FFT, ME/MC, and KLT look similar for both of 2-fold and 4-fold acceleration. However, we can clearly compare the accuracy of each method on the ROC curves in Fig. 4. k-t FOCUSS using KLT shows the best accuracy. k-t FOCUSS using KLT shows better performance than the control experiments in both accelerations.

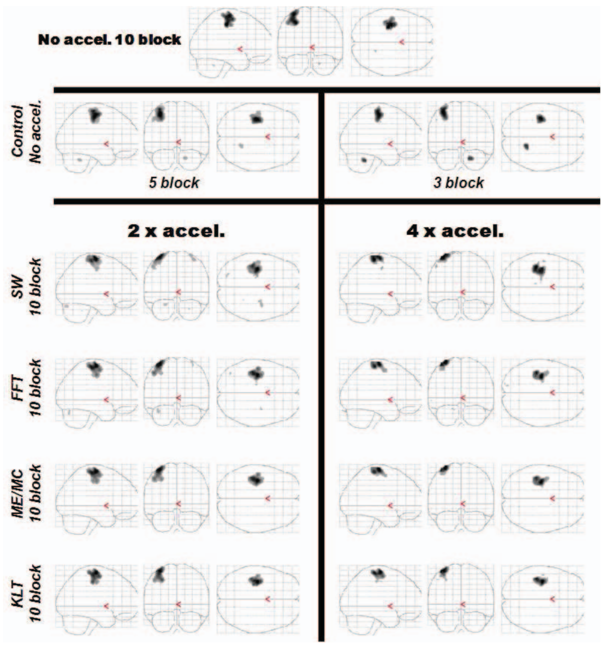
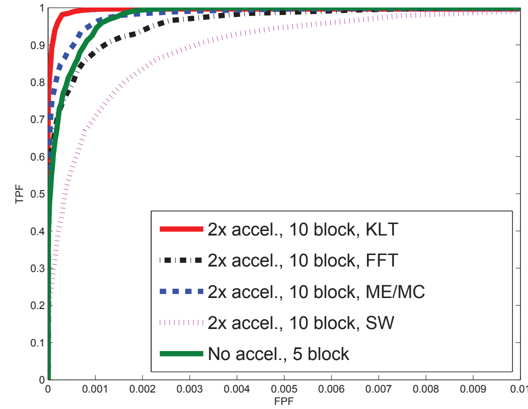


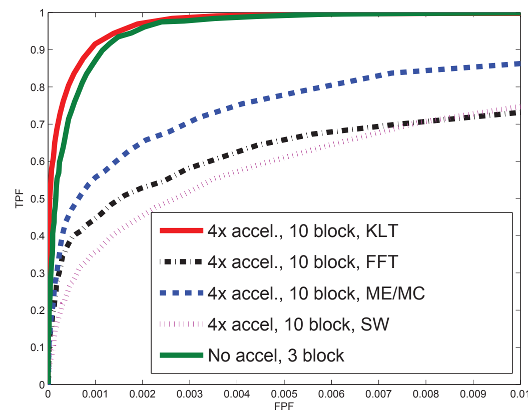
Fig. 3. Activated brain areas for various methods and acceleration ratio during the RFT task.

5. CONCLUSION

We confirmed that compressed sensing based accelerated fMRI using KLT basis shows very accurate results by increasing the number of blocks to make the total number of measurements comparable. Improving the temporal resolution is essential for broader use of fMRI. This paper provides a new way to extend the feasibility of fMRI to various fMRI studies such as event related cognitive study that usually requires very high temporal resolution.



(a)



(b)

Fig. 4. ROC plots for various methods; (a) 2-fold acceleration and (b) 4-fold acceleration.

6. REFERENCES

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