

HIGHLY ACCELERATED 3D DYNAMIC CONTRAST ENHANCED MRI USING PARTIAL SEPARABILITY MODEL AND JSENSE

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TARGET AUDIENCE: Scientists and clinicians interested in highly accelerated dynamic MRI

PURPOSE: Dynamic contrast enhanced (DCE) MRI requires high spatial resolution for morphological information and high temporal resolution for contrast pharmacokinetic modeling. The current fast imaging techniques [1-5] have shown success in improving the temporal resolution of DCE-MRI. However, it is still challenging to improve both the spatial and temporal resolutions simultaneously. This abstract presents a new approach to highly accelerated dynamic contrast enhanced MRI. Using a phased array coil, data was acquired continuously along a stack of variable-density spiral trajectories updated with the golden angle [6]. In reconstruction, the approach integrates parallel imaging [7,8] with the partial separable (PS) model [5,9,10] to obtain the image from highly undersampled data. The proposed method is evaluated on a set of in vivo dynamic contrast enhanced liver imaging data with prospective undersampling. The experimental results show that the proposed method is able to achieve high spatial and temporal resolutions at the same time.

THEORY AND METHODS: Model: The main goal of the proposed method is to recover the dynamic image sequence $\gamma(\mathbf{x}, t)$ from its under-sampled Fourier measurements acquired through multiple channels of a phased array coil, where \mathbf{x} and t represent spatial location and time respectively. We adopt the PS model which assumes $\gamma(\mathbf{x}, t)$ to be spatial-temporal partially separable [5,9,10]: $\Gamma^{M \times N} = [\gamma(\mathbf{x}, t_1), \dots, \gamma(\mathbf{x}, t_N)] = \mathbf{U}_s^{M \times R} \mathbf{V}_t^{R \times N}$, where \mathbf{U}_s and \mathbf{V}_t represent the spatial coefficient matrix and the temporal basis, and R is the rank of Γ . We further assume the dynamic image sequences to be sparse in the spatial and temporal frequency domain [10,11]. In addition, we exploit the coil sensitivity information in the imaging equation and assume the sensitivity is time varying. The coil sensitivities are represented using a polynomial parametric model at each channel and each time [8].

Problem formulation: Incorporating the above models, the image reconstruction problem is formulated as $\min_{\mathbf{U}_s, \mathbf{V}_t, \mathbf{a}_\ell} \sum_{\ell=1}^C \|\mathbf{d}_\ell - \mathbf{E}(\mathbf{a}_\ell)(\mathbf{U}_s \mathbf{V}_t)\|_2^2 + \lambda \|\text{vec}(\mathbf{U}_s \mathbf{V}_t \mathbf{F}_\ell)\|_1$, where the L_1 norm term enforces the sparseness in the spatial and temporal frequency domain, \mathbf{F}_ℓ represents the temporal Fourier transform, $\mathbf{E}(\mathbf{a}_\ell)$ represents an operator which integrates both the Fourier transform with a specified undersampling trajectory in (k, t) -space and the coil sensitivity modulation; \mathbf{d}_ℓ is the k -space data acquired from the ℓ -th channel. The vector \mathbf{a}_ℓ is the coefficient of a polynomial for the ℓ -th channel at all times.

Initialization: An initial temporal basis is first estimated from the central part of the undersampled spiral k -space data within a chosen radius. These data can be used to obtain the initial coil sensitivity maps as well as a series of low spatial resolution but high temporal resolution images, represented in matrix Γ_{LR} . Then the temporal basis \mathbf{V}_t can be obtained from the R dominant right singular vectors through the singular value decomposition (SVD) [9].

Alternating optimization: \mathbf{U}_s , \mathbf{V}_t , and \mathbf{a}_ℓ are calculated and/or updated by the following optimization functions alternately: $\hat{\mathbf{U}}_s = \arg \min_{\mathbf{U}_s} \sum_{\ell=1}^C \|\mathbf{d}_\ell - \mathbf{E}(\hat{\mathbf{a}}_\ell)(\mathbf{U}_s \hat{\mathbf{V}}_t)\|_2^2 + \lambda \|\text{vec}(\mathbf{U}_s \hat{\mathbf{V}}_t \mathbf{F}_\ell)\|_1$,

$\hat{\mathbf{V}}_t = \arg \min_{\mathbf{V}_t} \sum_{\ell=1}^C \|\mathbf{d}_\ell - \mathbf{E}(\hat{\mathbf{a}}_\ell)(\hat{\mathbf{U}}_s \mathbf{V}_t)\|_2^2 + \lambda \|\text{vec}(\hat{\mathbf{U}}_s \mathbf{V}_t \mathbf{F}_\ell)\|_1$, and $\hat{\mathbf{a}}_\ell = \arg \min_{\mathbf{a}_\ell} \|\mathbf{d}_\ell - \mathbf{E}(\mathbf{a}_\ell)(\hat{\mathbf{U}}_s \hat{\mathbf{V}}_t)\|_2^2$, all ℓ .

RESULTS: A 3D fast spoiled gradient echo stack of spirals sequence with partial Fourier slice encoding [6] was acquired in a liver donor patient (TR/TE=7.2/0.6 ms, FOV=360mm, slice thickness=5mm, matrix size = 256x256x36, 8 channel cardiac coil) after the injection of contrast. Consecutive spiral leaves are rotated by the golden ratio angle of 220° such that each new spiral leaf is sampling a substantially different part of k -space compared to the immediately preceding leaf. For each spiral leaf, a full set of slice encodings (partially encoded) is acquired. A variable density spiral trajectory was used where 48 spirals fully sample the k_x - k_y plane. Three such fully sampled volumes were acquired for a total scan time of 33s. In Fig. 1, we compare the proposed (PS-JSENSE) and the sliding-window (SW) methods when 15 and 48 consecutively acquired leaves are combined respectively. The temporal intensity curves of artery and inferior vena cava (IVC) are shown in Fig. 2. It is seen that the proposed method with 15 leaves is able to suppress the aliasing artifacts present in the sliding-window reconstruction with 15 leaves and achieve a better spatial resolution than the sliding-window reconstruction with 48 leaves. In addition, the small respiratory motion causes artifacts in SW 48 but no artifacts in PS-JSENSE with 15 leaves. The intensity curves also suggest that the proposed method is superior to the sliding-window method in preserving kinetic information.

CONCLUSION: We have proposed an approach to dynamic DCE imaging with high spatial and temporal resolution. The approach effectively combines JSENSE, PS, and sparsity constraints in the same framework. Using the prospectively undersampled liver DCE data, the proposed method has shown to achieve high resolution, artifacts-free reconstructions, while capturing the dynamics of the contrast pharmacokinetics.

REFERENCES: [1] Korosec FR, et al., MRM, 36:345–351, 1996. [2] Barger AV, et al., MRM, 48:297–305, 2002. [3] Mistry N, et al., MRM, 59:289–297, 2008. [4] Tsao J, et al., MRM, 50:1031–1042, 2003. [5] Brinegar C, et al., MRM, 64:1162–1170, 2010. [6] Xu B, et al., MRM, 69:370–381, 2013. [7] Pruessmann KP, et al., MRM, 42:952–962, 1999. [8] Ying L, et al., MRM, 57(6):1196–1202, 2007. [9] Liang ZP, ISBI: 988–991, 2007. [10] Zhao B, et al., IEEE Trans. Med. Imag., 31(9):1809–1820, 2012. [11] Jung H, et al., MRM 61:103–116, 2009.

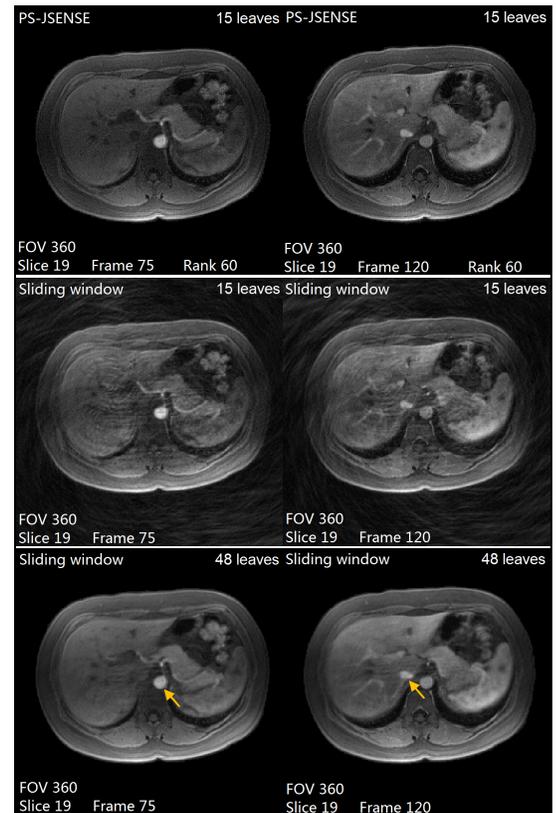


Fig. 1. Reconstructions of the proposed method (PS_JSENSE) and the sliding-window method with 15 and 48 leaves (Nyquist). Artery and IVC are indicated by the arrows in frames 75 and 120 respectively.

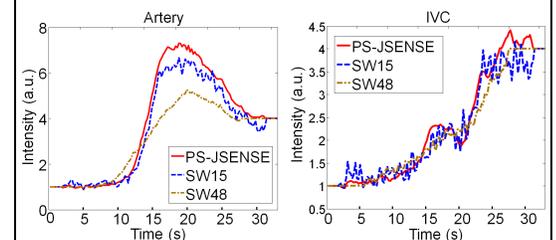


Fig. 2. The intensity vs. temporal frame curves of artery and IVC for three different reconstructions.