Fast 3D Free-breathing Abdominal Dynamic Contrast Enhanced MRI with High Spatiotemporal Resolution

Tao Zhang¹, Joseph Cheng^{1,2}, Marcus Alley², Martin Uecker³, Michael Lustig³, John Pauly¹, and Shreyas Vasanawala² ¹Electrical Engineering, Stanford University, Stanford, California, United States, ²Radiology, Stanford University, Stanford, California, United States, ³Electrical

rical Engineering, Stanford University, Stanford, California, United States, Radiology, Stanford University, Stanford, California, United States, Electrica Engineering and Computer Sciences, UC Berkeley, Berkeley, California, United States

Purpose: Dynamic Contrast Enhanced (DCE) MRI is commonly used to detect and characterize lesions. For 3D DCE MRI, a trade-off between spatial and temporal resolution is often necessary. A free-breathing DCE acquisition has high scan efficiency, but image quality can be compromised by respiratory motion. In this work, a soft-gated locally low rank parallel imaging method is proposed for free-breathing DCE MRI. The proposed method can significantly reduce motion artifacts and reconstruct highly undersampled DCE datasets with high spatiotemporal resolution (approximately 1 mm³ spatial resolution and 4 s frame rate). The proposed method has been validated on *in vivo* datasets.

Theory: DCE MRI can be accelerated by low rank methods^[1-4]: DCE images can be reformatted into a spatiotemporal matrix (Casorati matrix), where each column represents an image at one temporal phase. The data redundancy of DCE datasets is reflected by the low rank property of this spatiotemporal matrix. The spatiotemporal matrix has even lower rank when only a local region (image block) is considered^[5,6]. This is referred to as the locally low rank property. In free-breathing acquisitions, data inconsistency due to respiration will create motion artifacts such as image blurring. To reduce the motion artifacts, a soft-gating approach^[7,8] can be used: k-space data points are assigned with a motion weighting (ranging from 0 to

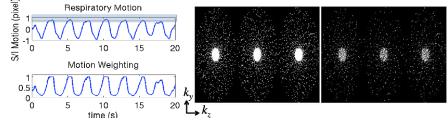


Fig.1 Left: (top) S/I respiratory motion measured by Butterfly (motion free region highlighted); (bottom) Corresponding motion weighting function. Middle: VDRad sampling patterns (first three temporal phases) before motion weighting (R=14.4). Right: VDRad sampling patterns after motion weighting. Inconsistent data points are assigned with small motion weighting.

1) according to the respiratory motion obtained from navigators. Data points with more motion are assigned with smaller data consistency weighting. Soft-gating, locally low rank, and parallel imaging can be combined to reconstruct highly undersampled free-breathing DCE datasets. For simplicity, a 2D acquisition is assumed, and the following variables are defined: m_t as the image at time t (size: $n_x \times n_y$), m as the entire DCE image series (size: $n_x \times n_y \times T$), y_t as a matrix of acquired k-space data from all coils at time t (size: $n_x \times n_y \times n_c$), S as the coil sensitivity (size: $n_x \times n_y \times n_c$), F as a Fourier transform operator, D_t as the undersampling operator at time t, C_b as an operator that takes a block of m (size: $b_x \times b_y \times T$) and reformats it into a

spatiotemporal matrix (size: $b_x b_y \times T$), and W_t as the soft-gating function. Then the reconstruction can be formulated as:

minimize_{*m*} $\Sigma_b ||C_b m||_*$, subject to: $||W_t(D_t FSm_t - y_t)|| < \varepsilon, t = 1, 2, ..., T$

where $||x||_*$ is the nuclear norm of matrix x and ε is the error. A projection onto convex sets type method was used to solve this problem. In this work, 16×16 image blocks were used. S was calculated using ESPIRiT^[9] from time-averaged data, and two sets of eigenvector maps were used in case of an overlapped field of view (FOV). The motion weighting was generated based on the respiratory motion measured by Butterfly^[10].

Methods: A 6-year-old patient was scanned on a 3T scanner using a 36-phase fat-suppressed 3D Butterfly sequence with variable density radial view ordering (VDRad)^[8] and a 32-channel cardiac coil. The acquisition parameters were: TR/TE = 3.0/1.2 ms, flip angle = 15° , matrix = $320 \times 180 \times 78$, FOV = $34 \times 27 \times 16$ cm³. The total acceleration factor per temporal phase was 14.4 and the frame rate was 4.07 s. Three reconstructions were compared: (1) frameby-frame soft-gated compressed sensing parallel imaging (softgated L₁-ESPIRiT^[8]); (2) locally low rank parallel imaging (locally low rank ESPIRiT.

<u>Results:</u> The measured respiratory motion and the corresponding weighting function are shown in Fig. 1. An example of the reconstructed image is shown in Fig. 2. Soft-gated L_1 -ESPIRiT suffered from severe image blurring due to high acceleration. Locally low rank ESPIRiT was also blurry because of respiratory motion. The proposed soft-gated locally low rank ESPIRiT method significantly reduced motion artifacts, reflected by the sharp delineation of the hepatic vein and stomach (arrows). The rapid

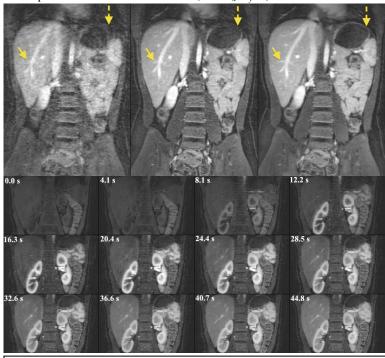


Fig.2 Top: Reconstructions of a 6-year-old patient by soft-gated L₁-ESPIRiT (left), locally low rank ESPIRiT (middle), and soft-gated locally low rank ESPIRiT (right). Bottom: Cropped images of the first 12 temporal phases from the soft-gated locally low rank ESPIRIT reconstruction.

contrast dynamics (liver, spleen, kidney, etc) were also captured and shown in Fig. 2. Together, this demonstrates the feasibility of depicting small rapidly enhancing structures in a small child with rapid hemodynamics during a free-breathing acquisition.

Conclusion: A soft-gated locally low rank ESPIRiT method has been proposed and validated for fast 3D free-breathing abdominal DCE MRI.

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