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Deep Radial Dynamic Contrast-Enhanced (DCE) MRI with Learned Variational Network in the Temporal Dimension

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Full Synopsis (100 words) and Impact (40 words)

Background: DCE-MRI plays a major role in cancer diagnosis and staging. To accurately quantify kinetic parameters in DCE-MRI, accelerated acquisition with advanced reconstruction is demanding. **Goal:** To develop a fast and efficient image reconstruction technique that learns a variational network in the temporal dimension for DCE-MRI based on continuous radial acquisition. **Approach:** While it is challenging to acquire fully sampled data for the variational network training, we simulated ground truth data based on the Tufts model. Moreover, the network we trained employs a 1D U-Net architecture to learn a regularization along the temporal dimension. **Results: Impact:** .

(main abstract: 750 words)

Background or Purpose

DCE-MRI has been routinely used in clinical practice to identify cancerous tissues. However, conventional DCE-MRI only acquires two images, one before the contrast agent injection, and another afterward, such as to visualize signal enhancements and hence fails to quantitatively extract pharmacokinetic parameters. To achieve this, continuous acquisition is required to capture during the procedure of contrast wash-in and wash-out. Recent developments of the GRASP technique [1] have shown substantial advances in DCE-MRI. GRASP combines rapid radial acquisition and compressed sensing reconstruction with temporal total variation (TV) regularization [2]. The TV model, however, is not generalized enough to capture rapid dynamic changes and tends to produce temporal smoothness. Therefore, we aim to develop a fast and efficient image reconstruction technique that learns a variational network [3] in the temporal dimension for DCE-MRI based on continuous radial acquisition.

Methods

Simulation of Training Data

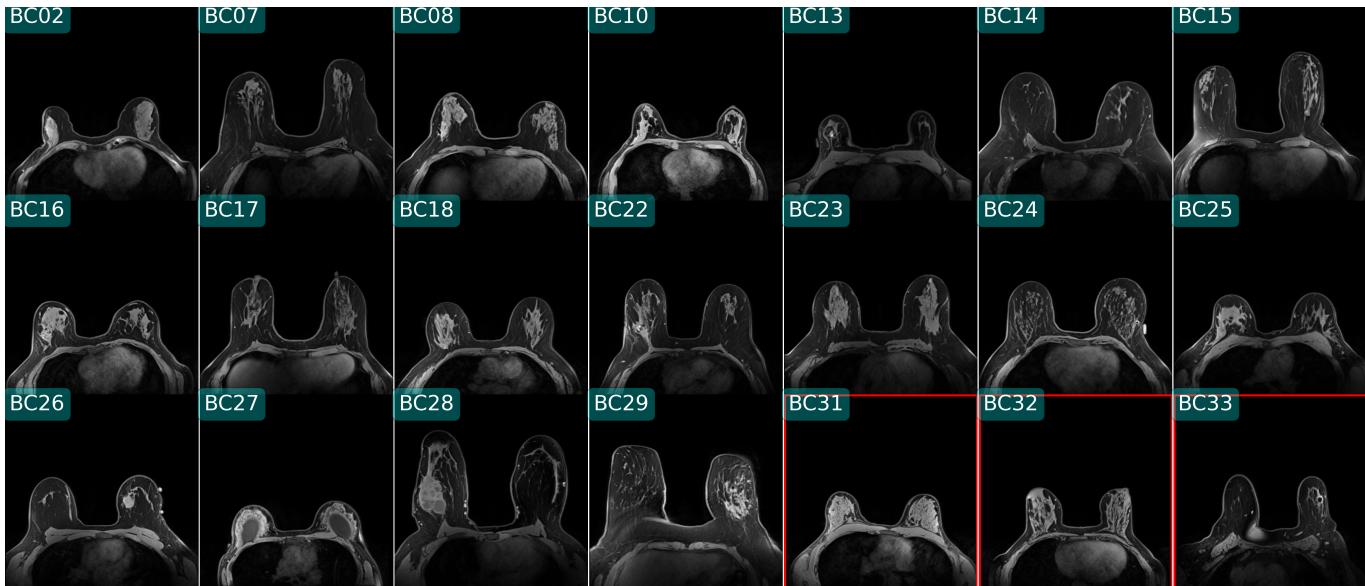


Figure 1. An overview of simulated data. The first 18 data were used for training, and the last three (in red boxes) were used for testing.

T1-weighted volumetric breast images were acquired by a 3D gradient-echo sequence at 3T (Siemens Healthineers, Erlangen, Germany). 21 subjects were selected for tissue segmentation, based on which various DCE signal generated by the Tofts model [3] were superimposed on different tissues.

Learning Variational Network (VN) in the Temporal Dimension

As proposed by Hammernik et al. [4], the update rule in VN consists of two steps: (1) the data consistency term $\|z - x^{(t)} - \lambda A^H(Ax^{(t)} - y)\|$, and (2) the model term $\|x^{(t+1)} - z - \mathcal{N}(z)\|$. Here, t denotes the cascade index, x is the image to be reconstructed, A is the MRI forward operator implemented by the torchkbnufft [5], y is the measured k -space data, and \mathcal{N} is the VN model parameterized by the parameter set θ .

We utilized the 1D U-Net [6] which operates along the temporal dimension to learn a temporal regularizer. Three layers were used for both the encoder and the decoder in U-Net, and each layer is constructed by a convolution block, consisting of 1D convolution, instance normalization, leaky ReLU, dropout, instance normalization, leaky ReLU, and dropout operators. The proposed network was optimized by ADAM [7] with a learning rate of 0.001 and the mean square error (MSE) loss function.

We

Results

Conclusions

References

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