Data-Driven Image Contrast Synthesis from Efficient Mixed-Contrast Sequences

Jonathan I Tamir[1], Valentina Taviani[2], Shreyas S Vasanawala[3], and Michael Lustig[1]

[1]*Electrical Engineering and Computer Sciences, University of California, Berkeley, Berkeley, CA, United States;*
[2]*MR Applications and Workflow, GE Healthcare, Menlo Park, CA, United States;* [3]*Department of Radiology, Stanford University, Stanford, United States*

Introduction: Synthetic MR aims to generate MR images with retrospectively chosen scan parameters[1]. Typically, these images are produced in two stages. First, data collected at multiple measurement times are reconstructed or fit to a physical-based model. The model may be explicit, e.g. with Bloch equations[1-4]; or it may be implicit, e.g. using subspace constraints[5-10]. Next, the result is used to synthesize image contrasts, e.g. through Bloch simulation or through linear combinations of the subspace images. The explicit approach leverages prior physical information and non-linear equation fits, but it may introduce error when the model does not adequately explain the data. The implicit approach benefits from a relaxed model constraint, but is limited in expressibility due to the linearity. Here we propose a two-step approach to contrast synthesis, inspired by ideas from the RAISR technique for image super-resolution[11]. First, we solve a regularized linear inverse problem to jointly reconstruct images at multiple measurement times. Second, we classify spatio-temporal patches into distinct classes and apply linear combinations tailored to each class. The two-step approach combines the robustness of regularized linear reconstructions with the expressibility of non-linear classification. As proof of principle, we apply the approach to increase the scan efficiency of proton-density (PD) volumetric fast spin-echo (3D FSE) imaging in the brain. We increase scan efficiency by acquiring at multiple, short TRs, a technique we call T1 Shuffling[8]. This reduces the echo train length (blurring) at the expense of T1-weighted contamination. We de-emphasize the T1 weighting and rec over a PD image by applying the proposed data-driven contrast synthesis. Fig. 1 summarizes the approach.

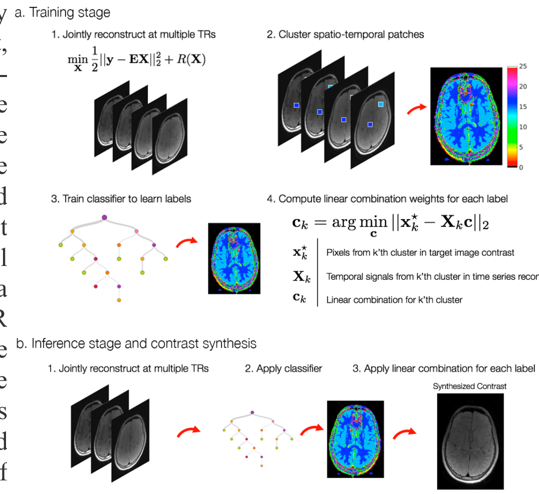

Fig 1. Overview of the method. a. At training, spatio-temporal patches are clustered, a classifier is trained to label new patches, and linear combinations are learned to map each cluster to a target contrast. b. At inference, a new time-series reconstruction is classified into labels, and each pixel is linearly combined according to its label.

Theory: A time series of images $\mathbf{X}$ is reconstructed from multi-channel k-space data, $\mathbf{Y}$, through a linear inverse problem: $\min_{\mathbf{X}} \|\mathbf{Y} - \mathbf{E}\mathbf{X}\| + R(\mathbf{X})$, where $\mathbf{E}$ is the SENSE-based[12] forward operator consisting of estimated coil sensitivities and optionally a subspace constraint, and R is a regularization term. Given a reconstruction $\mathbf{X}$ and a target image contrast $\mathbf{x}^\star$, spatio-temporal patches are extracted from the concatenation, $\overline{\mathbf{X}} = [\mathbf{X}\ \mathbf{x}^\star]$, normalized, and clustered with K-means, providing labels for each pixel in $\mathbf{x}^\star$. For each cluster, a linear combination is fit between the time series and the target value: $\mathbf{c}_k = \mathrm{argmin}_{\mathbf{c}} \|\mathbf{x}_k^\star - \mathbf{X}_k\mathbf{c}\|, k = 1, \ldots, K$, where $\mathbf{x}_k^\star$ and $\mathbf{X}_k$ are the pixels in $\mathbf{x}^\star$ and $\mathbf{X}$ with label k, respectively. After obtaining the clusters, a classifier is trained to map the spatio-temporal patches back to the corresponding labels. At testing time, a new reconstructed image is classified into labels using the classifier, and the precomputed linear combinations are applied to obtain the target image contrast.

Table 1. Acquisition parameters used for the 3D FSE scans.

Acquisition Type	3D non-selective	**Field of View**	24 × 24 × 18.7 cm³
Readout Direction	Sagittal	**Acquisition Voxel**	0.94 × 0.94 × 1.3 mm³
TE (ms)	15	**Acquisition Matrix**	256 × 256 × 144
Echo Spacing (ms)	3.86	**Slice Thickness (mm)**	1.3
Echo Train Length	29	**Number of Channels**	32

Methods: Two volunteers were scanned with IRB approval at 3T on a Siemens Trio, with a brain protocol consisting of separate 3D FSE acquisitions (Table 1, TRs = 288, 400, 1830, 2800 ms). The data were coil-compressed[13] to 12 channels and coil sensitivities were estimated using ESPIRiT[14]. The PD image, corresponding to TR = 2800, was chosen as the target image contrast, and the other three images were chosen as the time series. Using the first volunteer data, patches of size 3x3 were used for K-means with $K = 15$ clusters to create labeled images across 40 slices. A decision tree classifier was trained to map the spatio-temporal patches to the labels with 10-fold cross-validation. The images from the second volunteer were used for testing, whereby patches were classified into a label and the learned linear combination was applied. Image reconstructions were performed with BART[15] and clustering/classification was performed in MATLAB.

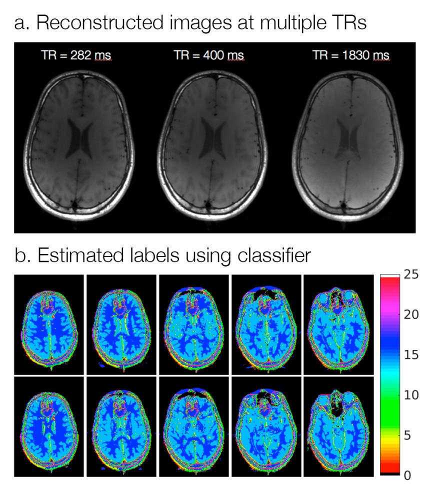

Fig 2. a. Reconstructed images at multiple TRs, used for testing. b. Estimated labels on 10 slices using the learned classifier.

Results and Discussion: Fig. 2a shows axial reconstructions of the three short TR scans from the second volunteer used for testing. Fig. 2b shows the label map after classification across 10 slices. Tissue with different spatio-temporal characteristics are clustered into distinct labels. Fig. 3 shows the target image contrast and the data-driven contrast synthesis for one of the 10 representative slices. The overall contrast is captured, though errors in classification lead to errors in contrast synthesis. We expect these errors to reduce as training data is increased to include multiple subjects. In conclusion, data-driven contrast synthesis may be useful for synthetic MR using acquisitions with varying measurement parameters.

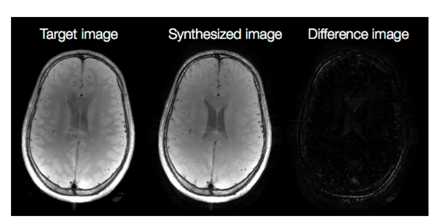

Fig 3. Target (left), synthesized (middle), and difference (right) PD-weighted images on a slice from the test data. The synthesized image shows good agreement with the target image, but has slightly reduced gray/white matter contrast.

References: **1.** Warntjes, MRM 60(2), 2008. **2.** Ma, Nature 495, 2013. **3.** Gomez, ISMRM 1167 2017. **4.** Zhao, ISBI 2015. **5.** Nataraj, arxiv 1710.02441, 2017. **6.** Huang, MRM 67(5), 2012. **7.** Tamir, MRM 77(1), 2017. **8.** Tamir, ISMRM 0231, 2017. **9.** Zhao, MRM 79(2), 2018. **10.** Asslander, MRM 79(1), 2018. **11.** Ramano, IEEE TCI 3(1), 2017. **12.** Pruessman, MRM 42(5), 1999. **13.** Zhang, MRM 69(2), 2013. **14.** Uecker, MRM 71(3), 2014. **15.** Tamir, Sedona Workshop, 2017.