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Processing Stack-of-Stars DCE Data

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We use this protocol and it's working

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Abstract

Step-wise protocol for reconstruction of Stack-of-stars acquired DCE series, T1 and B1 maps and PK (pharmacokinetic) modeling of DCE data using a reference region model is provided.

Reconstruction of Stack-of Stars (SoS) radial k-space sampled DCE data

1 Image reconstruction

1.1 VFA and AFI images

The same reconstruction procedure is used for images acquired by the variable flip angle (VFA) and actual flip angle (AFI) stack-of-stars (SoS) pulse sequences.

1. Apply a Fourier transform in the slice direction to separate slices
2. Shift image in the slice direction to match geometry of reference T2-weighted image
3. Apply the following corrections to each view:
   3.1. Center each view in k-space by moving its peak to the center of k-space
   3.2. Phase normalize
   3.2. Correct for off-resonance frequency using the average phase difference between views in opposite directions
4. Re-grid radial k-space data to a 128×128 Cartesian grid as described by O'Sullivan et al. To summarize, for each slice:
   4.1. Multiply signal of each point by its respective area on a Voronoi diagram of the points (including zerofill points) in k-space
   4.2. Re-grid each radially defined point to its nearest Cartesian coordinates using its Kaiser-Bessel index
5. Apply Fourier transform to now Cartesian-defined k-space

Citation

O'Sullivan, JD (1985)
. A Fast Sinc Function Gridding Algorithm for Fourier Inversion in Computer Tomography. IEEE Transactions on Medical Imaging.

10.1109/TMI.1985.4307723 LINK

1.2 DCE images

The k-space weighted image contrast (KWIC) method described by Song et al (2000 and 2004). was used to reconstruct the DCE images. To summarize, for DCE-MRI, the KWIC method uses radial acquisition's inherent oversampling of the k-space center by only

using a subset of the acquired views in that region. By using a sliding window to select the views that are included in that central region, multiple images can be created from a single acquisition of k-space, thus increasing the temporal resolution.

After applying the KWIC, the resulting k-space data is reconstructed using the same method as **1.1- VFA and AFI Images**.

Citation

Song HK, Dougherty L (2000)
. k-Space weighted image contrast (KWIC) for contrast manipulation in projection reconstruction MRI.
Magnetic Resonance in Medicine.

https://doi.org/10.1002/1522-2594(200012)44:6<825::AID-MRM2>3.0.CO;2-D LINK

Citation

Song HK, Dougherty L (2004)
. Dynamic MRI with projection reconstruction and KWIC processing for simultaneous high spatial and temporal resolution.
Magnetic Resonance in Medicine.

https://doi.org/10.1002/mrm.20237 LINK

2 **B1 field map generation from AFI images**

1. Compute pixel-wise actual flip angles using the equation

$$\alpha = \arccos\left(\frac{rn-1}{n-r}\right), \text{ where}$$

$$n = TR_2/TR_1 \text{ , and}$$

$r = S_1/S_2$, where

S_i is the signal intensity from the image acquired at TR_i .

2. Divide resulting actual flip angle maps by nominal flip angle to yield normalized pixel-wise B1 field maps.
3. Fit normalized B1 field maps to 3D 3rd degree polynomial using a least-squares fit to yield final B1 field maps used for T1 correction (step 3.1)

3 T1 map generation from VFA images

1. Compute T1 values using a non-linear least squares fit of the VFA image signal intensity to the Ernst equation

$$S(\alpha_{act}) = M_0\left(\frac{\sin\alpha_{act}\ (1-E_1)}{1-E_1\cos\alpha_{act}}\right)$$, where

$E_1 = e^{-TR/T_1}$, and

$\alpha_{act} = B1 * \alpha_{nom}$.

4 Generate tissue masks for reference region (muscle), kidney and tumor.

1. Open DCE images in an imaging processing software (eg. ImageJ)
Note: Images immediately following contrast agent injection tend to outline structures well. Anticipating slight movement of the slices either due to respiratory motion or due to other reasons, a T2-weighted scan is usually acquired before the DCE sequence and used for ROI masking.

2. Create a mask accessible by your analysis software which defines skeletal muscle and any other ROIs of interest.

For example, on ImageJ:
1. Create a new empty image with same dimensions as DCE image in File → New → Image
2. Draw ROIs by hand and add to ROI Manager by pressing shortcut "t"
3. Set ROIs in empty image to a values for each tissue by Process → Map → Set
4. Save as raw image by File → Save As → Raw Data

5 DCE metric map generation from DCE images

5.1 Compute contrast agent concentration time-course from signal time-course for each voxel and for spinal muscle (reference region)

For each voxel:
1. Compute actual (B1-corrected) flip angle at voxel using $\alpha = B1 * \alpha_{nom}$.
2. Normalize signal time course by mean signal prior to bolus injection

3. Compute T1 time-course using equation

$$T_1(t) = -TR \Big/ \ln\left(\frac{A - S_R(t)}{A - S_R(t)\cos\alpha}\right), \text{ where}$$

$$A = \frac{1 \; - \; e^{-TR/T_{1,0}}\cos\alpha}{1 - e^{-TR/T_{1,0}}} \text{ and}$$

$T_{1,0}$ is the baseline T1, obtained from the previously generated T1 map (step 3)

4. Estimate contrast agent concentration time-course using equation

$$C(t) = \left(\frac{1}{T_1(t)} - \frac{1}{T_{1,0}}\right) \Big/ R_{Gd}, \text{ where}$$

$R_{Gd} = 4.6/\mathrm{s} \cdot \mathrm{mM}$ (check for your specific contrast agent)

5.2 Compute spinal muscle (reference region) concentration time-course

1. Using a manually defined tissue mask for the spinal muscle, compute the mean concentration time-course for the entire muscle ROI

5.3 Compute quantitative DCE parametric maps

For each voxel:
1. Using the reference region model (Jones et al.) and the muscle as a reference tissue, fit for K^{trans} and v_e using the following equation:

$$\frac{dC_t}{dt} = \frac{K_t^{trans}}{K_m^{trans}}\frac{dC_m}{dt} \; + \; \frac{K_t^{trans}}{v_{e,m}}C_m \; - \frac{K_t^{trans}}{v_{e,t}}C_t, \text{ where}$$

the reference K^{trans} of muscle, $K_m^{trans} = 0.1/\mathrm{min}$,
the reference v_e of muscle, $v_{e,m} = 0.1$, and

C is the concentration of contrast agent, and the subscripts m and t refer to muscle (the reference region) and the tissue in the voxel being analyzed.

Note: K_m^{trans} and $v_{e,m}$ are reference values, therefore voxel K^{trans} and v_e values are relative to those assigned when fitting for the equation above. The values of $0.1/\min$ and 0.1 are from Cardenaz-Rodriguez et al.

Citation

Jones KM, Pagel MD, Cárdenas-Rodríguez J (2018)
. Linearization improves the repeatability of quantitative dynamic contrast-enhanced MRI.
Magnetic resonance imaging.

https://doi.org/10.1016/j.mri.2017.11.002 LINK

Citation

Cardenas-Rodriguez J, Howison CM, Pagel MD (2013)
. A linear algorithm of the reference region model for DCE-MRI is robust and relaxes requirements for temporal resolution.
Magnetic Resonance Imaging.

https://doi.org/10.1016/j.mri.2012.10.008 LINK

6 Obtaining ROI metrics from maps

While pixel-wise parametric maps allow us to assess heterogeneity of a specific metric within the tumor, we also compute all parameters (K^{trans},v_e) from the ROI of interest (tumor, kidney, and phantom):

1. Extract K^{trans} and v_e values for each voxel in the ROI.
2. Compute ROI metrics of choice (eg. mean, median, percentile values, standard deviation)

Note: To mitigate the impact of pixels whose K^{trans} and v_e values are outliers, we prefer median instead of mean of all pixels in the ROI.

Citations

Step 1.1

O'Sullivan, JD. A Fast Sinc Function Gridding Algorithm for Fourier Inversion in Computer Tomography
10.1109/TMI.1985.4307723

Step 1.2

Song HK, Dougherty L. k-Space weighted image contrast (KWIC) for contrast manipulation in projection reconstruction MRI
https://doi.org/10.1002/1522-2594(200012)44:6<825::AID-MRM2>3.0.CO;2-D

Step 1.2

Song HK, Dougherty L. Dynamic MRI with projection reconstruction and KWIC processing for simultaneous high spatial and temporal resolution
https://doi.org/10.1002/mrm.20237

Step 5.3

Cardenas-Rodriguez J, Howison CM, Pagel MD. A linear algorithm of the reference region model for DCE-MRI is robust and relaxes requirements for temporal resolution
https://doi.org/10.1016/j.mri.2012.10.008

Step 5.3

Jones KM, Pagel MD, Cárdenas-Rodríguez J. Linearization improves the repeatability of quantitative dynamic contrast-enhanced MRI.
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