Evaluation of Principal Component Model-based algorithm for T2 estimation of small objects

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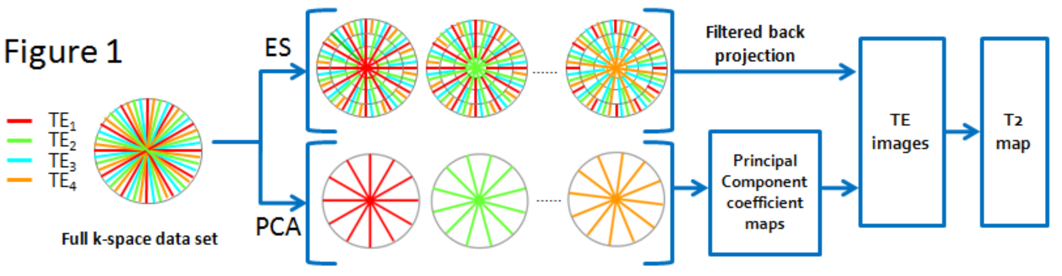
Introduction: Radial Fast Spin Echo (FSE) methods have been proposed for fast T2 mapping based on TE data sets generated from highly undersampled data. An echo sharing (ES) approach was developed to reconstruct TE images by partitioning k-space into data sets that are weighted to a specific TE. As shown in Figure 1, TE-weighting is obtained by leaving data at a specific TE in the center of k-space and adding data at other TEs moving towards the outer part of k-space. Due to the mixing of TE data in the ES approach, T2 estimation for small structures could be problematic (1).

Recently we have proposed a Principal Component Model-based algorithm (PCA) to reconstruct TE images from highly undersampled radial FSE data via principal component coefficient maps (2). As shown in Figure 1, in this algorithm we do not mix TE information; instead we use the various TE data in a model-based approach. As explained in (2), this approach also takes advantage of temporal and spatial sparsity of the model to improve the T2 estimation.

Figure 1



In this work, we will evaluate this algorithm based on the accuracy of T2 estimation for highly undersampled radial data under different conditions and compare it with the ES algorithm.

Methods: For quantitative comparisons a numerical phantom was used to conduct simulations. The phantom consisted of a circular object of varying diameter with T2=100 ms (representing typical malignant lesions) embedded in a larger circular uniform background with $T2_{background}$ = 0 ms (represents no background), 20 ms, 30 ms, 40 ms, 50 ms, 60 ms, 80 ms, 100 ms, 140 ms, 170 ms and 200 ms. K-space data for the phantom were generated using the analytic Fourier Transform of a circle using ETL=16, echo spacing=8 ms, acquisition matrix of 256(frequency)×256 (16 k-space lines per TE). Independent Gaussian noise was added to the real and imaginary components of k-space to produce an SNR comparable to *in vivo* data and 20 noise realizations were used to derive the statistics.

Physical phantoms containing 5 mm inner diameter glass tubes with agarose concentrations (weight %) of 0.6% and 1.2% were prepared (two of each). Two of the vials were embedded in a 2.4% agarose background and two were imaged without background. Data were acquired at 1.5T with ETL=16, echo spacing=8.29ms, TR=1s. The FOV was set to yield roughly 6-pixel diameter objects for the tubes, representing a 1 cm diameter lesion for in vivo abdominal imaging. The acquisition matrix of 256×256 yielded a total of 16 radial k-space lines for each of the 16 TE data sets. Gold standard data were acquired using the radial FSE method with 256 k-space lines per TE.

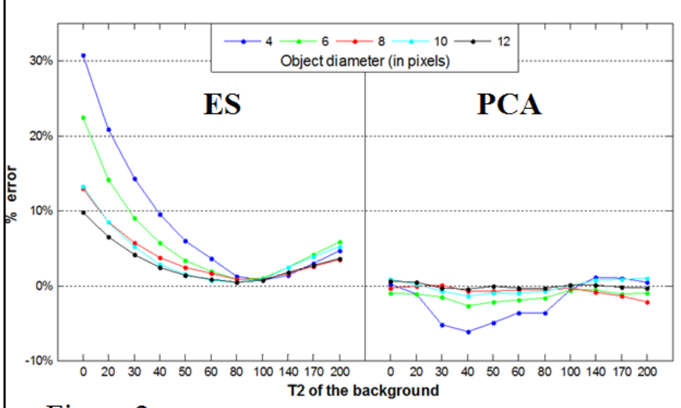
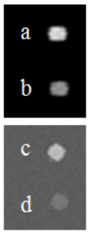


Figure 2

Results: Figure 2 shows the % bias of the T2 for small objects (true T2 =100 ms) of various diameters versus the T2 of the background. Note that for the ES algorithm the estimation is more accurate when the T2 of the background is closer to the T2 of the object. The error increases as the background T2 differs more from the T2 of the object, and is maximum when there is no background (represented by $T2_{background}$ = 0 ms). The error also depends on the diameter of the object. T2 estimates obtained with the PCA approach are less dependent on the background and object size.

The background independence of PCA T2 estimates is demonstrated in Figure 3 for a physical phantom. The figure shows images of the vials without (a, b) and with (c, d) background as well as the mean T2 estimates and % error (relative to the gold standard) for the ES and PCA algorithms. The radial FSE data used for T2 estimation with ES and PCA was 16 times undersampled with respect to the gold standard. Note that the % error of the T2s calculated by the ES algorithm changes with the background with a 7% increase between vials (a, c) and 10.4% between vials (b, d). T2 estimation with the PCA is less dependent on the background with only a 1.3% change between vials (a, c) and 0.9% between vials (b, d).

Figure 3



vial	Gold standard (ms)	PCA		ES	
		Estimated T2	% error of the mean	Estimated T2	% error of the mean
a	159.5	164.3	3.0	175.6	10.1
b	81.5	81.6	0.1	95.4	17.1
c	157.3	164.0	4.3	152.5	3.1
d	83.6	84.4	1.0	89.2	6.7

Conclusions and Discussion: In this work, we evaluate a PCA-based algorithm, recently developed for T2 estimation from highly undersampled radial data, and compare it to a previously developed ES approach. Experiments using numerical and physical phantoms show that the PCA-based algorithm yields T2 estimates that are more accurate for small objects and less dependent on the surrounding background.

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References: 1. Altbach MI, et al. MRM 54, 3(2005):p549 2. Huang C, et al. ISMRM 18 (2010):348