A comparative study of undersampling schemes for magnetic resonance dynamic contrast enhanced imaging

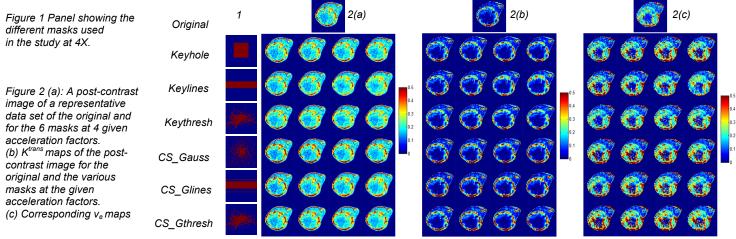
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Introduction: Dynamic contrast enhanced (DCE) imaging has been shown to provide critical information about tumor microvasculature. By measuring the concentration of the contrast agent in the blood and tissue over time, pharmacokinetic parameters like the contrast agent extravasation rate (K^{trans}) and the extravascular – extracellular volume fraction (v_e) can be determined. DCE requires high spatial and temporal resolutions which are conventionally in conflict. Accomplishment of high temporal resolution at a given spatial resolution requires reduction in acquisition time. One of such conventional acceleration schemes is the keyhole imaging technique (1) which is a simple and effective approach to accomplish higher temporal resolution at native spatial resolution. Another approach to accelerate DCE acquisition is by the use of compressed sensing(2). The DCE data is sparse in the spatio-temporal domains. Hence a cost function for a convex optimization problem is constructed as shown in {1} (adapted from reference 2). Here, I_{diff} is the desired difference image between the reference image and the intermediate image, F is the Fourier transform operator, F is the wavelet

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respectively, and € is the value of the cost function. An essential study is to compare the efficacy of the 2 techniques based on the factors of acceleration and the masks that are used for acquisition. Since compressed sensing involves incoherent sampling, it is essential to study the implication of choosing a particular sampling mask. Most importantly, the reconstruction techniques need to be evaluated based on the fidelity of reconstruction of the pharmacokinetic parameters which contain significant prognostic value.



Methods: DCE data of 5 breast tumor bearing rats were used to study the utility of each of the 2 approaches. The data sets had dimensions of 64 X 64 and 64 images were acquired with a temporal resolution of 12 seconds. OmniscanTM (0.1 mmol/kg) was intravenously administered through the tail vein. Algorithm implementation and data processing were performed using MATLAB (The Mathworks Inc., MA). *Keyhole methods*: 3 different keyhole approaches classified on the shape of the sampling mask were implemented. The first one contained a square centered at the center of k-space (Keyhole) while the second was a number of phase-encode lines in the center of k-space (Keylines). The third mask was based on the locations above a specific threshold of the absolute value of k-space of the pre-contrast image (Keythresh). The reconstruction for each case was compared with the full k-space reconstruction quantified by RMSE. *Compressed sensing based methods*: Compressed sensing based reconstructions were performed based on 3 different masks. The first mask involved the use of points in k-space with a high density weighting at the center of k-space based on the Gaussian probability distribution function (pdf) (CS_Gauss) while the second involved phases-encode lines based on the Gaussian pdf (CS_Glines). The third mask was essentially the same mask as Keythresh (CS_Gthresh). For the study, these masks were generated for acceleration factors of 2, 3, 4 and 5 respectively. The masks used for the reconstructions at an acceleration factor of 4X can be seen in figure 1(a). *Pharmacokinetic analysis*: The signal intensity time course was converted to corresponding concentrations of the contrast agent which was then utilized to generate maps of the pharmacokinetic parameters of K^{rans} and v_e based on reference region method of quantification of DCE pharmacokinetic parameters(3). These maps were generated for the complete k-space reconstruction method, keyhole imaging methods as well as the reconstructions based on compressive sensin

Results: The image panel in figure 1(b) shows the quality of reconstruction of a representative DCE data set resulting from the 6 different approaches at the given acceleration factors. For the shown data set, the compressed sensing methods over estimate the pixel intensity values at lower acceleration factors. It can be observed that the loss in contrast and edge information at acceleration factors of 4 and 5 in the compressed sensing based methods significantly lesser than the keyhole methods. The maps of two fundamental parameters of K^{trans} for a representative data set for the implemented acceleration factors and approaches are shown in figure 2(a). For the K^{trans} maps, it can be noted that the compressive sensing approaches based on CS_Gthresh over-compensate for acceleration factors of 2X and 3X for the representative data set shown. CS_Glines and CS_Gauss show consistent performance over the chosen acceleration factors. Among the keyhole approaches, it can be observed that the calculation of these maps begin to fail at an acceleration factor of 3X and beyond. V_e maps generated from the six reconstruction approaches at the 4 acceleration factors for the representative data set are shown in the figure 2(b). As in the case of K^{trans} maps, the CS_Gauss and CS_Gthresh based approaches over-compensate for v_e maps awell. The mean RMSE values for each of the 64 temporal points for the 5X case follow the trend: Keylines > Keythresh > Keyhole > CS_Gauss > CS_Gthresh > CS_Glines. Comparatively, the compressed sensing based approaches perform consistently better than the keyhole approaches with the exception of Gauss mask for this representative data shown.

Conclusion and future work: It has been shown here and previously that DCE MRI can be reliably accelerated through methods like compressed sensing and keyhole reconstructions to obtain increased spatial and/or temporal resolution. Compressive sensing based approaches involve implementation of sophisticated pulse sequences in some cases but are comparatively more robust as determined by the quantification of errors for reconstruction. Future work involves segmentational analysis of the tumor data and statistical analyses of the different masks withthe full k-space reconstruction as the control.

Reference: 1)Vanvalls JJ, et al. JMRI 1993 3(4):671-675 2)Jim J, et al. Proc. of IEEE Intl. Symposium on Biomedical Imaging 2008:1613-1616 3)Yankeelov TE et al. MRI;23(4):519-29 Acknowledgment: Grant support from UL1RR024982, R21CA132096-01A1, W81XWH-05-1-0223