A Digital Perfusion Phantom for T1-weighted DCE-MRI

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INTRODUCTION: T1-weighted Dynamic Contrast-Enhanced MRI (DCE-MRI) is a popular technique for the characterization of tumors and other pathological tissue. It requires coverage of large imaging volumes at high spatial and high temporal resolution, which remains challenging even with modern MRI equipment and usually requires a trade-off between both. For a higher temporal resolution, keyhole and view-sharing techniques help to obtain images by undersampling k-space and filling the missing samples with data acquired at different points in time. Recently, novel Compressed Sensing methods have been proposed that promise very high undersampling factors in the spatial as well as temporal domain [1,2]. However, it is unclear if these advanced reconstruction techniques preserve the true dynamics of the contrast enhancement, which otherwise could have significant impact on the quantitative analysis of the contrast-agent kinetics. In the latter case, a noisy image that reflects the true underlying dynamics would be more favorable than a beautified image that shows less noise and undersampling artifacts but deviates from the true course of contrast enhancement.
To investigate these effects, we developed an extension to the well-known analytical Shepp-Logan phantom in the temporal dimension to simulate contrast enhancement in arteries and in healthy and pathological tissue. Unlike image-based approaches [3], a k-space based phantom allows for accurate sampling along arbitrary trajectories [4]. This enables assessing the influence of k-space sampling strategies as well as the evaluation of reconstruction techniques for dynamic imaging. MATLAB source code for the phantom as well as for the generation of the contrast dynamics will be made available online at http://www5.cs.fau.de/research/software/dippo-mri/ .

MATERIALS AND METHODS: The phantom is based on the well-known Shepp-Logan model and extended by different ellipses to represent arteries as well as healthy and pathological tissue. The model can be sampled at arbitrary k-space locations, and because independent intensities can be assigned to the ellipses for each point in time, different contrast dynamics can be modeled for any trajectory. Contrast enhancement in tissue is simulated using the Tofts and Kermode model [6]. According to this model, the contrast agent concentration $C_t(t)$ in tissue and at time t is computed as:

$$C_t(t) = v_p C_p(t) + K^{trans} \int_0^t C_p(\tau) e^{-(t-\tau)\cdot k_{ep}} d\tau,$$

where v_p is the fractional volume of blood plasma in tissue, K^{trans} the transfer constant, and $k_{ep} = K^{trans} / v_e$. v_e represents the fractional volume occupied by extravascular extracellular space in tissue. $C_p(t)$ denotes the blood plasma concentration or arterial input function (AIF), which we implemented using the Parker model and, alternatively, the Weinmann model [5]. User-defined AIFs can be used in the phantom as well. By assuming a T_1 relaxation time that is proportional to the contrast agent concentration, the observed signal enhancement can be computed from the contrast agent concentration.
As a first application, we used the phantom to investigate effects of different acquisition schemes for radial k-space sampling. The contrast dynamics were simulated during the acquisition of 377 radial spokes over 200 seconds. Arterial enhancement was computed based on the Parker AIF and the contrast enhancement in healthy and tumor tissue [6] using (K^{trans},v_e)=(0.88 min^{-1}, 143%) and (0.26 min^{-1}, 36%), respectively. We compared a uniform angular increment of 0.4775° per spoke (377 spokes over 180°) against an increment of 111.25°, which is also known as the golden angle scheme [7].
In the second experiment, we used a CG-SENSE based iterative reconstruction approach and investigated the impact of an initial image on the obtained contrast dynamics. The acquisition of 377 radial spokes with golden-angle reordering was simulated using the parameters described above. 14 frames were reconstructed using a sliding data window of 55 spokes with an increment of 24 spokes between frames. We compared the signal in the artery (indicated by yellow arrow in Fig. 2c) as well as the relative tissue enhancement in tissue (red arrows) obtained with conventional gridding to the signal obtained with the iterative reconstruction. The algorithm was initialized with a temporally averaged image (Fig. 1b), and 20 iterations were performed without application of additional regularization.

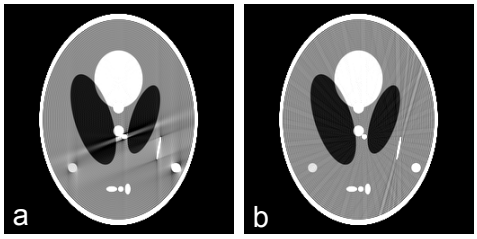

Fig. 1: Influence of radial reordering schemes: a) incremental, b) golden-angle reordering.

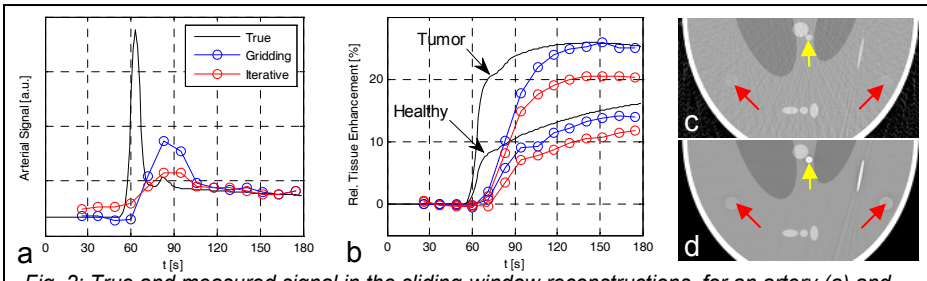

Fig. 2: True and measured signal in the sliding-window reconstructions, for an artery (a) and tissue (b). First frame obtained (c) with gridding and (d) with the iterative reconstruction.

RESULTS AND DISCUSSION: Fig. 1 compares the images acquired with different radial reordering schemes. The gradual increment of the first trajectory results in smearing artifacts that are also typical e.g. for perfusion CT imaging [8], while the golden-angle increment results in sharper but overall less prominent artifacts. The latter approach is favorable, as the smearing artifacts severely distort the vicinity of contrast-enhanced tissue.
Results of the second experiment are shown in Fig. 2. The ground truth signal in the artery and the relative enhancement in tissue are shown as solid black lines in Fig. 2a and b. As expected, the time course extracted from the gridding images (blue color) corresponds to the signal average over the sliding data window, which results in a delay and an underestimated arterial peak enhancement but otherwise acceptable curves. In the iterative reconstruction (red color), the use of the initialization image causes a distortion of the signal, which results in an over-smoothed curve shape and temporal bleeding effects, i.e. an artificial arterial signal increase before the actual bolus arrival. The relative enhancement plateau is underestimated for both healthy and tumor tissue. This is also visible in Fig. 2c) and d) that show the gridding and iterative reconstructions of the first frame. The iterative reconstruction shows less undersampling artifacts but the signal in the arteries as well as the healthy and pathological tissue (red arrows) is clearly overestimated. This example illustrates that it is important for quantitative DCE-MRI analysis to be aware of potential distortions that advanced reconstruction techniques might introduce, as visual appearance itself is not necessarily a reliable indicator for image accuracy anymore.

CONCLUSION AND OUTLOOK: In this work we presented an analytical perfusion phantom that helps to assess the accuracy of advanced reconstruction methods for dynamic MR imaging. First applications showed that the influence of the reconstruction technique can be significant, which indicates that these methods have to be used carefully when high temporal fidelity is desired. Future work will include the extension to 3D imaging as well as the incorporation of coil-sensitivity profiles [4] to further study the impact of parallel imaging components.

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