

# A Model-based Image Reconstruction Algorithm for Saturation Prepared Radially Acquired Data

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## Introduction

In MR parameter mapping, typically a suitable magnetization preparation is applied, followed by the acquisition of a certain number of images. In the presence of short relaxation times however, sampling the signal evolution with multiple images is difficult or even not possible. The measurement has to be performed in segmented fashion or with low spatial resolution.

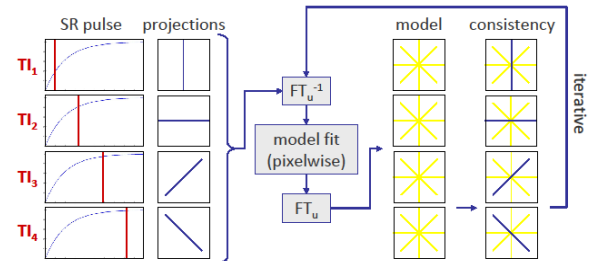
In this work we propose an iterative model-based image reconstruction in conjunction with radial data acquisition, capable to fully resolve an exponential signal evolution. Using an analytical linear regression algorithm, one complete image is reconstructed for each single radial projection acquired after a saturation recovery (SR) magnetization preparation.

## Material and Methods

For every pixel, the signal  $S(t)$  after a saturation recovery magnetization preparation can be modeled by a mono-exponential function:

$$S(TI) = S_0 (1 - \exp(-TI/T1_{eff}))$$

$T1$  indicates the time after the saturation pulse,  $T1_{eff}$  the apparent relaxation time of the tissue in presence of RF excitation and  $S_0$  the steady state signal. Utilizing the model as prior knowledge allows to characterize  $S(TI)$  by only the two parameters  $S_0$  and  $T1_{eff}$ . By performing image acquisition with a radial trajectory, every acquired projection contains information about the image contrast that can be utilized in a model-based image reconstruction to fully resolve the evolution of the signal with one image for each acquired radial projection.

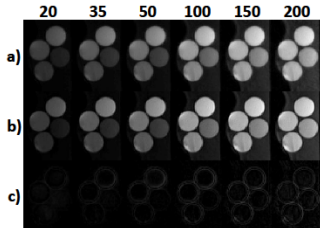


**Fig. 1:** Basic reconstruction scheme. Projections acquired after the SR pulse are blue, the reconstructed projections yellow.  $FT_u$  denotes an undersampled Fourier transform.

For image reconstruction, every single projection of the radially acquired k-space data was gridded onto a Cartesian grid using self-calibrating GROG (1) and Fourier transformed into image space. Subsequently, an iterative analytical linear regression fitting algorithm was applied pixel by pixel, in order to find the signal model with the least squares difference to the measured data (Fig. 1). Thus, during each iteration, a new model image was created for each acquired projection. In order to ensure data consistency, each originally measured projection was substituted into the k-space of its model image. The resulting images were used for the following iteration.

Phantom experiments were performed on a 3T whole-body scanner (Magnetom TRIO, Siemens AG Healthcare Sector, Erlangen, Germany) using a Saturation-Recovery SSFP sequence (FOV = 250 x 250 mm<sup>2</sup>, TE = 1.72 ms, TR = 3.44 ms, flip angle 50°) and a Golden Ratio (2) radial k-space trajectory with 202 radial projections and 128 readout samples. In order to acquire a fully sampled reference dataset for each time point  $T1$ , 202 measurements were carried out, the trajectory of each rotated by the golden angle with respect to the previous measurement. This complete dataset was retrospectively undersampled and the above described algorithm was applied to obtain one model image for every acquired radial projection. These were compared a conventional GROG reconstruction of the fully sampled reference.

In-vivo measurements were carried out on a clinical 1.5T whole-body scanner (Magnetom Avanto Siemens AG Healthcare Sector, Erlangen, Germany) using the same sequence, magnetization preparation and trajectory (FOV = 320 x 320 mm<sup>2</sup>, TE = 1.28 ms, TR = 2.6 ms,  $T_{acq}$  = 190 ms, flip angle 50°, 64 projections, 128 readout samples). Again, the proposed algorithm was used to reconstruct 64 images from the acquired 64 radial projections.

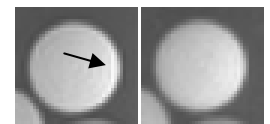


**Fig. 2:** Phantom measurements. **a)** Reconstruction from under-sampled data. **b)** Fully sampled reference. **c)** Difference.

## Results

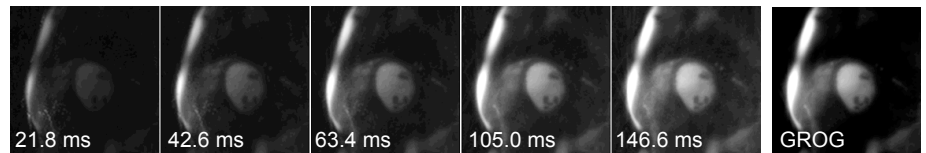
Fig. 2 shows images of the phantom, reconstructed for the different time points  $T1$  after the magnetization preparation using the proposed algorithm (a), the corresponding fully sampled reference images (b) as well as their difference (c).

Small signal differences are observed at the boundaries of the phantom. Figure 3 shows an enlarged section of the phantom, revealing Gibbs ringing artifacts (arrow) that are much less pronounced in the model-based reconstruction explaining the signal differences in Fig. 2. Results of the in-vivo measurements are depicted in Fig. 4. Shown are images reconstructed from one single radial projection acquired at the specified time point after the



**Fig. 3:** Reference image with Gibbs artifacts (left) and model-based reconstruction (right)

saturation recovery magnetization preparation (Fig. 4 left). The images reveal the same image quality as the image reconstructed by gridding all corresponding 64 projections using self-calibrating GROG (Fig. 4 right).



**Fig. 4:** In-vivo measurements.

## Discussion

The proposed model based algorithm allows the reconstruction of highly undersampled data in the presence of signal relaxation. With one fully reconstructed image for every acquired radial projection, the method provides an excellent temporal resolution of the signal recovery, which cannot be resolved with conventional reconstruction techniques. However, the presented approach requires an accurate model of the signal evolution in order to avoid systematic errors. The proposed technique is suitable for the reconstruction of various signals, e.g. T2-decays. Moreover, as the signal model comprises the relaxation parameters, the presented technique is considered to allow fast MR parameter mapping.

## References

- [1] Seiberlich, Magn. Reson. Med. 59:930-935 (2008)
- [2] Winkelmann, IEEE Trans. Med. Imaging 16:68-76 (2007)