

Patch-Based Reconstruction Of Undersampled Images (PROUD) for Sub-second Frame Rate 4D Contrast Enhanced Liver Imaging

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TARGET AUDIENCE Clinicians and researchers interested in high temporal frame rate 3D contrast enhanced dynamic liver imaging.

PURPOSE

High temporal & spatial resolution 4D imaging with large volume coverage is needed to accurately capture organ perfusion. Typically, parallel-imaging reconstruction is done to achieve high frame rate and large volume coverage and results in a loss of signal to noise ratio compared to Nyquist sampling. Furthermore, residual undersampling artifacts are temporally varying and complicate the quantitative analysis of contrast enhancement curves needed for pharmacokinetic modeling. Here, we propose a method, Patch based Reconstruction Of Undersampled Data or PROUD, that will both improve noise characteristics as well as minimize temporally-varying residual artifacts. The algorithm was tested in numerical phantoms and in vivo.

METHODS

To achieve high temporal & spatial resolution, data is acquired using a golden angle 3D stack of variable density spiral sequence [1] and a new time frame is reconstructed for each acquired spiral leaf. The basic PROUD reconstruction algorithm is inspired by the dictionary based method [2]. A reconstruction of a fully sampled data set at the beginning of the dynamic data (typically before the arrival of contrast) is performed to obtain an initial image v_0 . For each time t , we assume that every $n \times n$ patch $R_{ij}v_t$ around pixel (i, j) in frame v_t can be written as a linear function of exactly one patch in an $m \times m$ $P_{ij}v_{t-1}$ neighborhood around the same pixel (i, j) of the reference image v_{t-1} (where $m \geq n$). The last step replaces the potentially expensive search for a "learned dictionary" from an entire image, such as those obtained with the KSVD algorithm. This constraint leads to the following minimization problem to obtain a solution v_t^* for each time:

$$v_t^* = \operatorname{argmin}_{v_t} \|U_t F S v_t - y_t\|^2 + \lambda \sum_{ij} \|R_{ij} v_t - \alpha_{ijt} P_{ij} v_{t-1}^* - \beta_{ijt}\|^2.$$

The obtained images v_t^* then serve as the initial guess for the full inverse problem to be solved here:

$$v_{t=1, \dots, N}^* = \operatorname{argmin}_{v_{t=1, \dots, N}} \sum_t \|U_t F S v_t - y_t\|^2 + \lambda \sum_{ij} \|R_{ij} v_t - \alpha_{ijt} P_{ij} v_{t-1} - \beta_{ijt}\|^2 + \gamma \sum_t \|v_t - \frac{1}{2}(v_{t-1} + v_{t+1})\|^2.$$

Both minimization are solved as described in [2]. To test this algorithm, a numerical phantom was created with randomly generated noise (Fig. 1). The phantom was reconstructed with PROUD and the non-linear TRACER algorithm [1]. For in-vivo performance, five candidate liver donors were imaged with a 3D dynamic multi-phase spiral LAVA sequence [2,3] during gadolinium contrast administration. Images were reconstructed with both PROUD and TRACER. A contrast-to-noise ratio (CNR) was computed as $CNR = (S_{AO} - S_{PV})/N_L$, where S_{AO} and S_{PV} is the average signal in a ROI in the aorta and portal vein, respectively, and N_L the signal standard deviation in an ROI of homogenous liver tissue near both the aorta and portal vein ROIs. This is a measure for how well the arterial phase is visualized.

RESULTS

Fig. 2 shows temporal ROI curves reconstructed with PROUD from the noisy phantom data compared to the TRACER and the true noisy data. Both PROUD and TRACER have a similar temporal lag compared to the reference. However, PROUD reduces the high frequency variations of the signal due to the time varying residual undersampling artifacts. PROUD and TRACER images from liver donor candidates were reconstructed with one temporal frame per acquired spiral leaf (212 ± 47 ms/frame). An axial section of the 3D volume from one candidate is shown in figure 3. For five cases, in vivo average maximum CNR was 51 ± 29 for PROUD compared to 26 ± 12 for TRACER ($p=.04$). A nearly twofold improvement in CNR was seen using PROUD. An example CNR curve over time from one candidate is shown in figure 4.

DISCUSSION

The preliminary data in this work show the feasibility of the proposed PROUD method to reduce the noise and residual undersampling artifacts in high frame rate dynamic image reconstruction. A significant improvement in aorta to portal vein CNR was demonstrated, indicating an improved visualization of the hepatic arterial phase necessary for the detection and diagnosis of liver tumors. The signal enhancement curve showed reduced artifactual oscillations due to the further suppression of undersampling artifacts.

CONCLUSION

Patch based Reconstruction Of Undersampled Data (PROUD) is very promising for high spatial & temporal resolution 4D imaging.

REFERENCES

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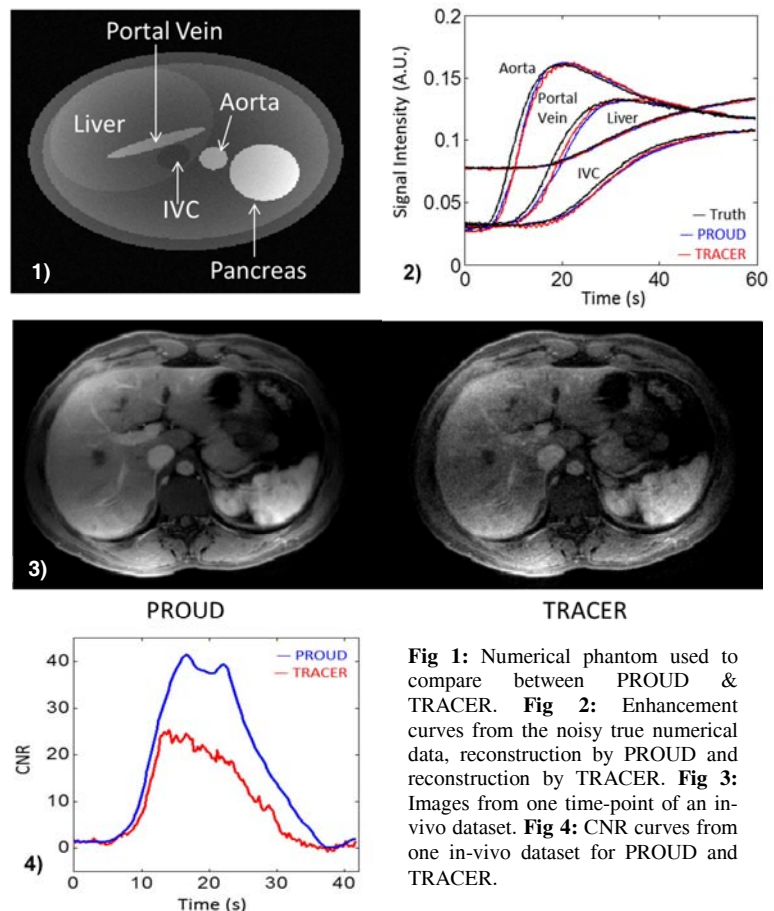


Fig 1: Numerical phantom used to compare between PROUD & TRACER. **Fig 2:** Enhancement curves from the noisy true numerical data, reconstruction by PROUD and reconstruction by TRACER. **Fig 3:** Images from one time-point of an in-vivo dataset. **Fig 4:** CNR curves from one in-vivo dataset for PROUD and TRACER.