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Introduction: The concept of nonlinear inversion was recently introduced for parallel imaging and shown to yield improved reconstruction quality [1]. This reconstruction strategy can be used for arbitrary sampling trajectories, but the specific structure of undersampling artifacts arising from the different trajectories was not exploited in the reconstruction problem up to now. This work describes an approach to include additional a-priori knowledge in the reconstruction process. Variational L1 penalties, which are known to facilitate removal of aliasing artifacts from undersampled radial and pseudorandom sampling patterns [2,3], are integrated in the nonlinear inversion method.

Theory: It was shown in [1] that parallel imaging by means of nonlinear inversion can be solved with an iteratively regularized gauss-newton (IRGN) method. This approach can be extended to include arbitrary regularization terms. With F being the operator that maps the unknown spin density u and the set of coil sensitivities $c=(c_1, \dots, c_N)$ (N being the number of receive coils) to the measured k -space data g , in each iteration step k for given $x^k:=(u^k, c^k)$ the minimum $\delta x=(\delta u, \delta c)$ of

$$\min_{\delta x} \frac{1}{2} \|F'(x^k) \delta x + F(x^k) - g\|^2 + \frac{\alpha_k}{2} W(c^k + \delta c) + \beta_k R(u^k + \delta u)$$

has to be computed for given $\alpha_k, \beta_k > 0$ and an initial guess x^0 , and then setting $x^{k+1} := x^k + \delta x$, $\alpha_{k+1} := q_\alpha \alpha_k$ and $\beta_{k+1} := q_\beta \beta_k$ with $0 < q_\alpha, q_\beta < 1$. Here, $F'(x_k)$ is the Jacobian of F evaluated at x_k , W is an operator such that the high Fourier coefficients of the sensitivity components of x are penalized and R is a regularization term on the image component. In this work, the total variation (TV), as well as total generalized variation (TGV) [4,5] are used for R . Numerically, this problem can be solved using a projected primal-dual extra-gradient method [6]. In the following, we refer to reconstructions with TV and TGV constraints as IRGN TV and IRGN TGV, respectively.

Methods and Results: Experiments were performed at 3T for radial (rf-spoiled radial FLASH, TR/TE=2.0/1.3 ms, FA=8°, matrix=128×128, 2 times oversampling resulting in 256 samples for each spoke, in-plane resolution 2mm×2mm, slice thickness 8mm, 32-channel body array coil) and pseudorandom (3D FLASH, TR/TE=20/5ms, FA=18°, matrix=256×256, resolution 1mm×1mm×1mm (in vivo measurements) and 1mm×1mm×5mm (phantom measurements), 12 channel head coil). In-vivo radial data acquisition was performed without cardiac gating and during free breathing. The results of conventional IRGN, IRGN TV and IRGN TGV for pseudorandom sampling with an acceleration factor of R=10 of a phantom are displayed in Fig. 1. Radially subsampled phantom measurements with 25 spokes are shown in Fig. 2. Figure 3 shows IRGN and IRGN TV reconstruction results of pseudorandom subsampling of the brain of a healthy volunteer with an acceleration factor of R=4. Results from undersampled radial cardiac measurements using 25, 21 and 19 spokes are displayed in Fig. 4.

Discussion: The results from this work demonstrate that pronounced improvements in reconstruction quality of parallel imaging with nonlinear inversion can be achieved with additional L1 based regularization. If moderate acceleration is used (Fig. 3), these penalties serve as a stabilization term against noise amplification which is inevitable in parallel imaging. Note that since β_k tends to zero, the final reconstruction does not show the typical cartoon like-features of TV-filtering. In cases when acceleration is pushed to its limits (Figs. 1, 2, 4) the final amount of regularization has to be increased (here, by setting $\beta_{k+1} = \max(q_\beta \beta_k, 5 \cdot 10^{-3})$) to facilitate additional removal of undersampling artifacts. However, it must be noted that in this case, small image features with low contrast may also be removed during the reconstruction. This effect can be observed for some smaller vessels in Fig. 4. The proposed approach is flexible and allows an easy exchange of the used penalty functional. This is demonstrated in Figs. 1 and 2, where additional reconstructions were performed with a TGV penalty. It can be seen that using a TV penalty leads to pronounced staircasing artifacts in regions with smooth signal changes because the assumption of piecewise constance is violated. This effect is reduced noticeably with TGV regularization.

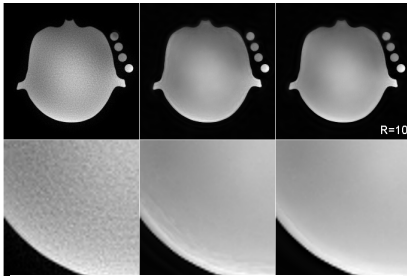


Fig. 1: Phantom measurements of pseudorandom subsampling with R=10. IRGN (left), IRGN TV (middle) and IRGN TGV reconstructions, $\beta_{min}=5 \cdot 10^{-3}$.

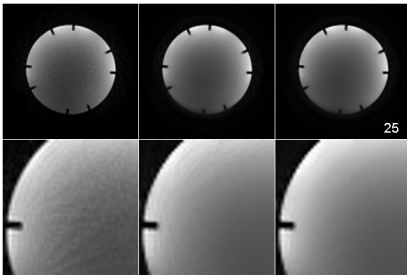


Fig. 2: Subsampled radial phantom measurements, 25 spokes. IRGN (left), IRGN TV (middle) and IRGN TGV reconstructions, $\beta_{min}=5 \cdot 10^{-3}$.

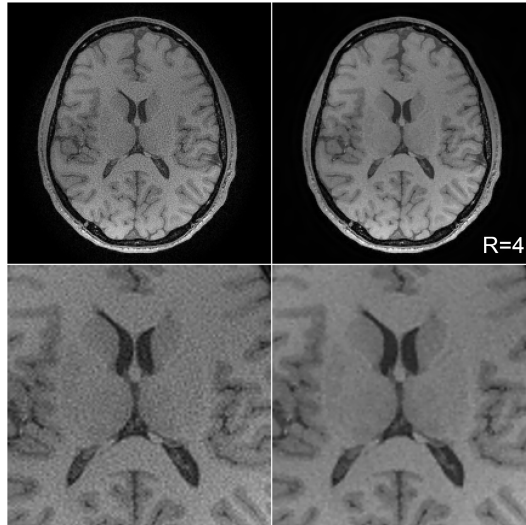


Fig. 3: Reconstructions of pseudorandom sampling, brain data set. IRGN (left) and IRGN TV (right). Acceleration factor R=4, $\beta_{min}=0$.

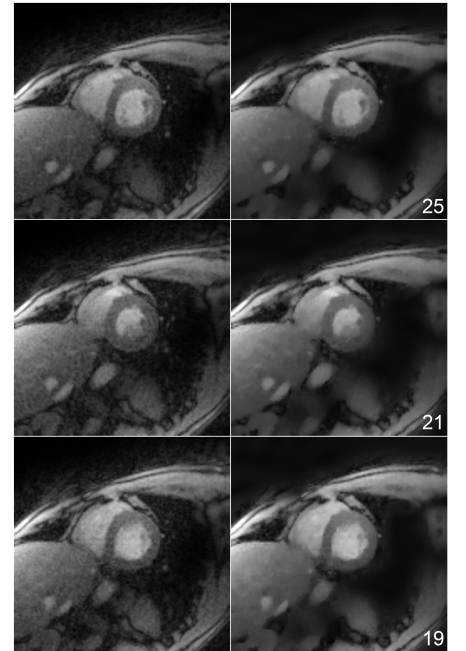


Fig. 4: IRGN (left) and IRGN TV (right) reconstructions of radial rt-FLASH cardiac data. 25 (top), 21 (middle) and 19 (bottom) spokes were used for the reconstruction of a 128×128 image, $\beta_{min}=5 \cdot 10^{-3}$.

References: [1] Uecker et al., MRM 60: 674-682, [2] Block et al., MRM 57: 1086-1098 (2007), [3] Lustig et al., MRM 58: 1182-1195 (2007), [4] Knoll et al., MRM (accepted, in production), [5] Bredies et al., SIAM Journal on Imaging Sciences 3(3): 492-526 (2010), [6] Pock et al., International Conference on Computer Vision (ICCV): 1133 – 1140 2009.