Highly undersampled time resolved phase-contrast MRA with flow-adapted compressed sensing reconstruction

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Introduction: Recently proposed combinations between iterative Compressed Sensing (CS) techniques [1] and parallel MRI reconstruction algorithms such as SENSE [2] achieve significant accelerations in MRI acquisitions. Especially multi-dimensional data acquisition techniques such as temporally resolved velocity-encoded phase contrast MRI (ve-PC MRI), typically associated with long acquisition times, could benefit from these accelerations. The assessment of three-dimensional velocity information requires four different MR scans X_s, a velocity-compensated one and three with flow encodings in all spatial directions. These are typically used to calculate three phase difference images and, finally also allow for the calculation of an angiographic image **PC**, which shows flow regardless of its direction [3]. The acquired dataset is five-dimensional (three spatial dimensions, temporal dimension and velocity encodings) and should contain a lot of redundancy, which renders the application ideally suited for CS. The method presented in this work combines an interleaved undersampled acquisition pattern with a temporal regularization that is adapted to the regions relevant for flow acquisition. Therefore high undersampling factors (USF) are supported preserving the original contrast-to-noise ratio (CNR) as well as the temporal resolution. The results achieved with this technique are compared to those of state-of the art methods such as SENSE and GRAPPA.

Material and Methods: In order to make optimal use of the data redundancies, all temporal phase and velocity encodings are reconstructed simultaneously. A recently proposed sampling pattern, combining a regularly undersampled central k-space region with a decreasing density towards the periphery [4] is used in an interleaved fashion along the velocity encoding and temporal directions. This allows the generation of an approximated **PC** image **PCa,** which is used to differentiate between flow regions and stationary tissue. For the temporal regularization, the transformation Ψ multiplies the difference between neighboring phases with **PCa**. The full target function (Eq. 1) consisting of the data fidelity term (including the pattern **U**, the Fourier coefficients **F** and the coil profiles **C**) and the temporal regularization added over all temporal phases is minimized using a Quasi-Newton method.

$$\vec{\hat{x}} = \underset{\vec{x}}{\operatorname{argmin}} \sum_{p}^{N_p} \sum_{s}^{N_s} \sum_{j}^{N_c} \left|\left| \mathbf{U}_s^p \mathbf{F} \mathbf{C}_j \vec{x} - \vec{y}_{s,j}^{\,p} \right|\right|_2^2 + \alpha \sum_{p}^{N_p} \Psi(\vec{x}^p) \quad \textbf{(1)}$$

4D PC MRI data were acquired on a clinical 3T MR scanner (MAGNETOM Skyra, Siemens Healthcare, Erlangen) in four healthy volunteers with an ECG-triggered sequence (TR=49.76ms, TE=3.50ms, flip angle 20°, FOV 200^2 mm^2, slice thickness 4mm, imaging matrix 256^2). For each patient a fully sampled dataset was acquired as well as a GRAPPA and a SENSE dataset using the product sequence with USF 6 and external reference lines. The fully sampled dataset was retrospectively undersampled with USF 6.1.

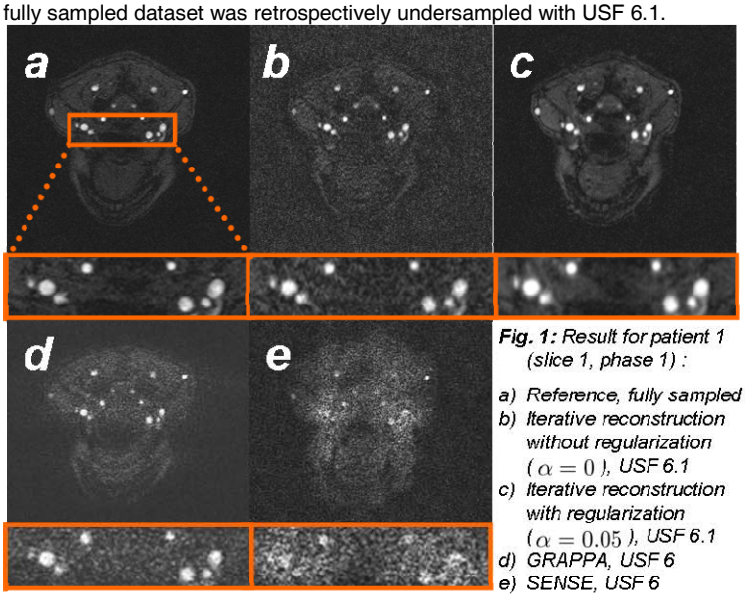

Fig. 1: Result for patient 1 (slice 1, phase 1) :
a) Reference, fully sampled
b) Iterative reconstruction without regularization ($\alpha = 0$), USF 6.1
c) Iterative reconstruction with regularization ($\alpha = 0.05$), USF 6.1
d) GRAPPA, USF 6
e) SENSE, USF 6

	Method	IFFT	reg off $\alpha = 0$	reg on $\alpha = 0.05$	GRAPPA	SENSE
	Sampling	full	USF 6.1	USF 6.1	USF 6	USF 6
Pat. 1	CNR_{VT}	6.58	5.61	7.86	3.74	2.12
	CNR_{VB}	3.09	0.90	3.52	1.80	1.55
Pat. 2	CNR_{VT}	14.06	8.93	12.06	4.51	1.74
	CNR_{VB}	18.17	9.47	14.69	5.31	1.81
Pat. 3	CNR_{VT}	12.90	8.47	14.06	5.36	1.10
	CNR_{VB}	17.08	8.22	16.39	6.36	3.00
Pat. 4	CNR_{VT}	14.90	10.67	13.13	3.02	1.78
	CNR_{VB}	4.67	1.36	6.06	0.62	0.42

Table 1: CNR results for patient datasets 1 – 4.

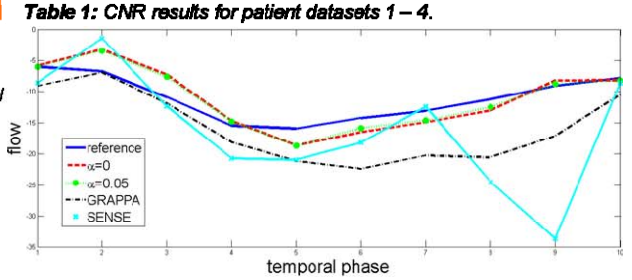

Fig. 2: Flow profile results

Results and Discussion: Reconstruction results from patient 1 (here the flow-compensated magnitude image) can be found in Fig. 1. While the unregularized iterative reconstruction result (b) illustrates the noise amplification both in the tissue and in the background, the visual impression of the regularized iterative reconstruction (c) is excellent and comparable to the fully sampled reference (a). The GRAPPA result (d) shows noisy regions especially around the vessel structures and the SENSE reconstruction leads to an overall noisy image. These observations are confirmed by the quantitative results in table 1: The CNR tissue/background value declines from 6.58 / 3.09 (reference) to 5.61 / 0.9 without regularization, while the regularized iterative method is able to get values even slightly superior to the reference case (7.86 / 3.52). The results for GRAPPA (3.74 / 1.80) and SENSE (2.12 / 1.55) show a drop of more than 50% compared to the reference. Concerning the flow quantification, Fig. 2 shows quantitative flow plots for all five reconstructions. While SENSE fails to retrieve the flow profile and while GRAPPA underestimates the flow peaks, the proposed iterative reconstruction yielded flow curves close to those of the reference results.

Conclusion: The proposed iterative CS technique for velocity-encoded phase contrast MRI proved to offer a robust and reliable reconstruction. For the same USF, it significantly outperformed classical state-of-the-art reconstruction methods such as SENSE and GRAPPA, regarding both contrast and flow accuracy. Next steps include extending the regularization of all spatial dimensions, which could further accelerate the PC measurements.

References: [1] Donoho, IEEE Trans. Inf. Theo. 2006; 52:1289 [2] Pruessmann et al., MRM 2001; 46:638 [3] Chai et al., J CMR 2005; 7:4:705 [4] Hutter et al., ESMRMB 2011; 24:92

The authors gratefully acknowledge funding of the Erlangen Graduate School in Advanced Optical Technologies (SAOT) by the German Research Foundation (DFG) in the framework of the German excellence initiative.

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