

New Image Reconstruction Methods for Accelerated Quantitative Parameter Mapping and Magnetic Resonance Angiography

This content has been downloaded from IOPscience. Please scroll down to see the full text.

2016 J. Phys.: Conf. Ser. 677 012002

(<http://iopscience.iop.org/1742-6596/677/1/012002>)

View [the table of contents for this issue](#), or go to the [journal homepage](#) for more

Download details:

IP Address: 92.63.65.142

This content was downloaded on 01/12/2016 at 10:42

Please note that [terms and conditions apply](#).

You may also be interested in:

[Function Projective Synchronization for Two Gyroscopes under Specific Constraints](#)

Min Fu-Hong

[MAT-MI acoustic source reconstruction using ultrasound B-Scan imaging](#)

L Mariappan, X Li, G Hu et al.

[Image reconstruction method for electrical capacitance tomography](#)

Xiangyuan Dong and Shuqing Guo

[Does thorax EIT image analysis depend on the image reconstruction method?](#)

Zhanqi Zhao, Inéz Frerichs, Sven Pulletz et al.

[The influence of the property of random coded patterns on fluctuation-correlation ghost imaging](#)

Chenglong Wang, Wenlin Gong, Xuehui Shao et al.

[Solution of the relativistic Dirac–Hulthén problem](#)

A D Alhaidari

[Exact solutions of the Manning–Rosen potential plus a ring-shaped like potential for the Dirac equation: spin and pseudospin symmetry](#)

S Asgarifar and H Goudarzi

[mathcal{P} symmetry as a generalization of Hermiticity](#)

Qing-hai Wang, Song-zhi Chia and Jie-hong Zhang

[Multi-frequency parameter mapping of electrical impedance scanning](#)

Ruigang Liu, Xiuzhen Dong, Feng Fu et al.

New Image Reconstruction Methods for Accelerated Quantitative Parameter Mapping and Magnetic Resonance Angiography

J V Velikina¹, A A Samsonov^{2,3}

¹Department of ¹Medical Physics, University of Wisconsin-Madison, Madison, USA

² Department of Radiology, University of Wisconsin-Madison, Madison, USA

³ Neurobiology Lab, Research Institute of Biology and Biophysics, Tomsk State University, Tomsk, Russian Federation

E-mail: alex0259@yandex.ru

Abstract: Advanced MRI techniques often require sampling in additional (non-spatial) dimensions such as time or parametric dimensions, which significantly elongate scan time. Our purpose was to develop novel iterative image reconstruction methods to reduce amount of acquired data in such applications using prior knowledge about signal in the extra dimensions. The efforts have been made to accelerate two applications, namely, time resolved contrast enhanced MR angiography and T1 mapping. Our result demonstrate that significant acceleration (up to 27x times) may be achieved using our proposed iterative reconstruction techniques.

1. Introduction

Magnetic Resonance Angiography (MRA) is an attractive non-invasive imaging choice that has shown utility in visualizing vasculature and blood haemodynamics. MRA is general term comprising a number of imaging techniques, including both single image and time-resolved imaging with or without the use of contrast agents. While many of MRA techniques may benefit from increased spatial and/or temporal resolution, time-resolved contrast-enhanced (CE) imaging often is in a particular need of acceleration. Indeed, in many diseases useful information can be gleaned from separate images of arterial and venous enhancement, hence rapid passage of contrast puts a bound on the acquisition time of a single frame, depending on application. For instance, such pathologies as intracranial arterial-venous malformations may require temporal resolution on the order of 0.5 - 1 s [1], while imaging of upper and lower extremities would benefit from 3-7 second frames [2]. At the same time, inherently low speed of MR acquisitions limits the number of k-space samples that can be acquired within a given time period. This duality creates a typical for MRA need for a tradeoff between spatial resolution/coverage on one hand and temporal resolution on the other hand. An attempt to maintain both high spatial and temporal resolution inevitably leads to the need to reconstruct images from incomplete data. Quantitative parameter mapping is another area of MRI that can often benefit from acceleration, albeit for different reasons. The need to acquire k-



space data for different values of control parameters often makes total acquisition time too long, increasing probability of patient motion. Since conventional reconstruction from undersampled data produces aliased images and SNR degradation, advanced imaging techniques are needed to address this problem.

The required acceleration can be achieved on either acquisition side (e.g., by using efficient non-Cartesian trajectories [3-5] or specialized Cartesian acquisitions [6-8]) or reconstruction side (e.g. by using constrained reconstruction). Often, the two are developed jointly to maximize the benefits, as is done in the recently developed compressed sensing (CS) technique [9], which provide a way to reconstruct images that admit a sparse representation from incomplete incoherently sampled data.

2. Theory

3. The problem of reconstructing image series \mathbf{f} is a system of linear equations $\mathbf{E}\mathbf{f} = \bar{\mathbf{b}}$, where \mathbf{E} is the encoding matrix, and $\bar{\mathbf{b}}$ is the vector of measured k-space data for all time frames. If k-space data is incomplete, the above equation has infinitely many solutions. To isolate a single solution, prior information about the image series is invoked to constrain the solution. Standard CS approaches exploit sparsity of the image series after application of general transforms \mathbf{D} , such as wavelets or spatial/temporal gradients [10-12], implemented through minimization of a cost function: $\min_{\mathbf{f}}(\|\mathbf{E}\mathbf{f} - \bar{\mathbf{b}}\|_2 + \lambda\|\mathbf{D}\mathbf{f}\|_1)$ Equation (1), whose size is measured by l_p norms ($\|\mathbf{x}\|_p^p = \sum |x_n|^p$), with the balance between the data consistency term (first summand) and the penalty term (second summand) adjusted by the size of regularization parameter λ . Still, if the underlying image series is not sparsified efficiently by the transform \mathbf{D} , the reconstruction may be biased towards the assumed behavior or suffer from unresolved aliasing artifacts. Therefore, proper choice of the transform \mathbf{D} is an important factor. In this work, we propose to consider two different types of transforms: a general transform \mathbf{D} equal to the second discrete derivative in temporal dimension and a data-driven one obtained by performing principal component analysis (PCA) of the training data. The first type of transform relies on the smoothness of temporal/parametric curves, which can be efficiently sparsified by double differentiation [13]. The second approach, termed Model Consistency COndition (MOCCO) [14], relies on linearized representation of non-linear operators mapping between image space and space of MR parameters. Such linearization is obtained by applying PCA to compress a set of analytical curves derived from a theoretical signal model equation or a low-resolution estimate of a time series obtained from a more fully sampled k-space center. Similar to other principal component basis (PCB) techniques [15,16], MOCCO assumes that temporal behaviour of most pixels can be approximated well by a linear combination of several waveforms. However, it allows for deviations from the chosen model as follows. Let (\mathbf{w}_k) be the set of chosen representative waveforms that span a linear subspace \mathbf{W} of waveforms satisfying the model assumption. Let \mathbf{S} be a synthesis operator mapping a set of coefficients (c_k) to a linear combination $\sum c_k \mathbf{w}_k \in \mathbf{W}$; and \mathbf{S}^* be its adjoint analysis operator yielding coefficients of projection of an arbitrary waveform w onto \mathbf{W} , $\mathbf{S}^*:w \rightarrow \langle w, \mathbf{w}_k \rangle$. If the model assumption is satisfied for a given pixel, then its temporal waveform w is "close" to \mathbf{W} , so $\mathbf{S}\mathbf{S}^*w \approx w$. Thus, the choice of $\mathbf{D} = \mathbf{S}\mathbf{S}^* - \mathbf{I}\mathbf{d}$ provides requisite sparsity of the image series, while the use of l_1 norm provides robustness of the reconstruction to outliers, for instance, due to pathologies.

4. Methods

Fully sampled datasets were acquired using hybrid radial (in-plane)/Cartesian (through-plane) SPGR sequence (TR = 5.5 ms, BW = 125kHz, 20 slices, 8 coil receivers) for a set of 12 flip angles

FA=[2°,3°,4°,5°,6°,7°,8°,9°,10°,12°,14°,16°] in a single scan session on a 3T scanner (MR 750, GE Healthcare; Waukesha, WI). The acquired data for a single central slice was retrospectively undersampled to simulate an interleaved undersampled radial acquisition with an acceleration factor of 20. The twelve interleaves were scheduled according to bit-reverse ordering. The images were obtained from the undersampled data by solving equation (1) with $\mathbf{D} = \Delta^2$. For comparison purposes, we also reconstructed images from the undersampled data using gridding with density compensation and iterative SENSE. Also, we used a pair of ideal flip angles for this case (calculated to be 3° and 16°) and the number of projections that could be acquired within the same scan time (100 projections per image) to assess the improvement in T1 estimation accuracy for the given scan time. As a reference, images from fully sampled data for all 12 flip angles were reconstructed. T1 values were then estimated from each set of the reconstructed images using non-linear minimization [17].

MOCCO reconstruction was validated in a CE exam from an intracranial aneurysms patient conducted according to the IRB at our institution. The patient was scanned on a 3.0 T clinical scanner (Discovery TM MR750, GE Healthcare, Waukesha, WI) with an 8-channel head coil using a hybrid radial (in-plane)/Cartesian (through-plane) acquisition during a contrast injection. The scan parameters were TE/TR=1.5/4 ms, FA=25°, BW=125 kHz, 20 slices, voxel size 0.86x0.86x2 mm³. The data were reconstructed from 15 radial projections per slice per 1.2 s time frame (acceleration factor R=27) using iterative SENSE [18], strictly constraining PCB different number of principal components and the proposed method with both l_1 -norm and l_2 -norm in the penalty term. Reconstructed images were compared for image quality and temporal waveform fidelity.

5. Results

Results of R1 (1/T1) estimation are given in figure 1. The proposed approach provided the best accuracy due to lower noise level, better artefact reduction and higher spatial resolution in the reconstructed images. The increase in the standard deviation measured in a region in white matter was measured to be 2.13 times for the proposed reconstruction versus 3.82 in the SENSE reconstruction from 2 ideal flip angles (both relative to the reference fully sampled data).

Images in figure 2 show limited maximum intensity projections of two early time frames for the four reconstruction techniques. Note that while all three constrained reconstruction techniques provide good spatial resolution and adequate SNR, the algorithms relying on l_2 -norm regularization exhibit premature enhancement of some vessels. This observation is further confirmed by examining temporal waveforms of the aneurysm and its feeding artery in figure 3.

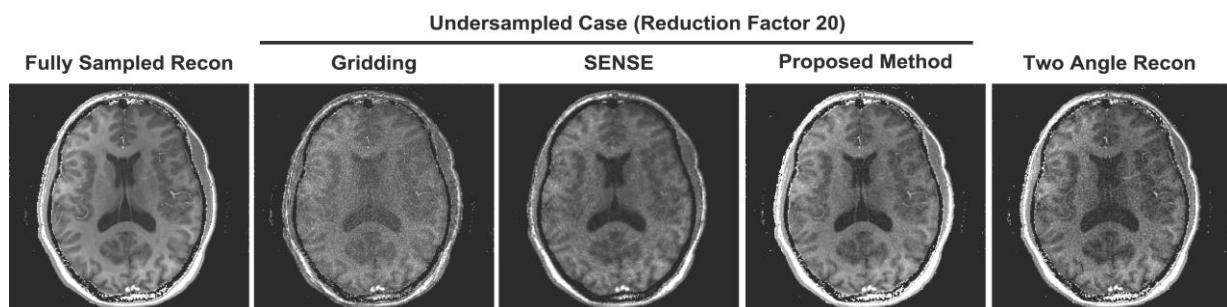


Figure 1. Reconstruction of T1 maps using different methods including proposed reconstruction and scan time equivalent two flip angle approach.

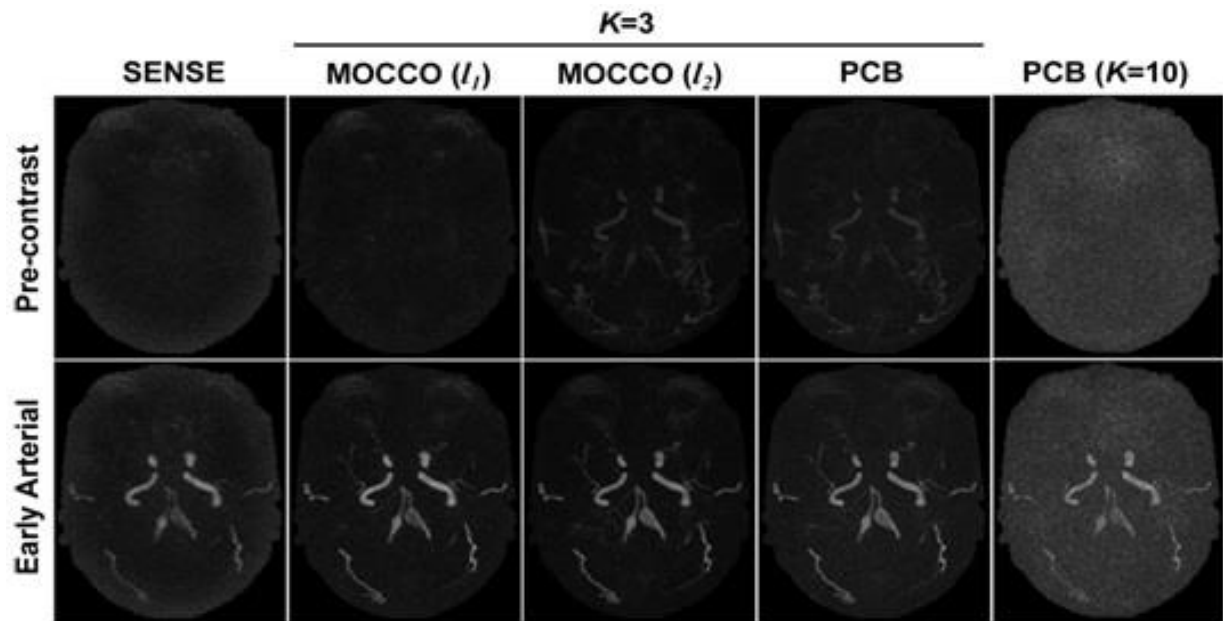


Figure 2. Time frames at 2.4 s (top row) and 7.2 s (bottom row) after the beginning of examination.

6. Conclusions

The proposed approaches exploiting sparsity of the image series in temporal/parametric dimension showed ability to improve image quality of accelerated acquisitions compared to parallel imaging/quadratic norm-based methods. In CE MRA applications, temporal dynamics in both normal and pathological vessels was preserved. In quantitative parameter mapping, the proposed method improved accuracy of parametric maps.

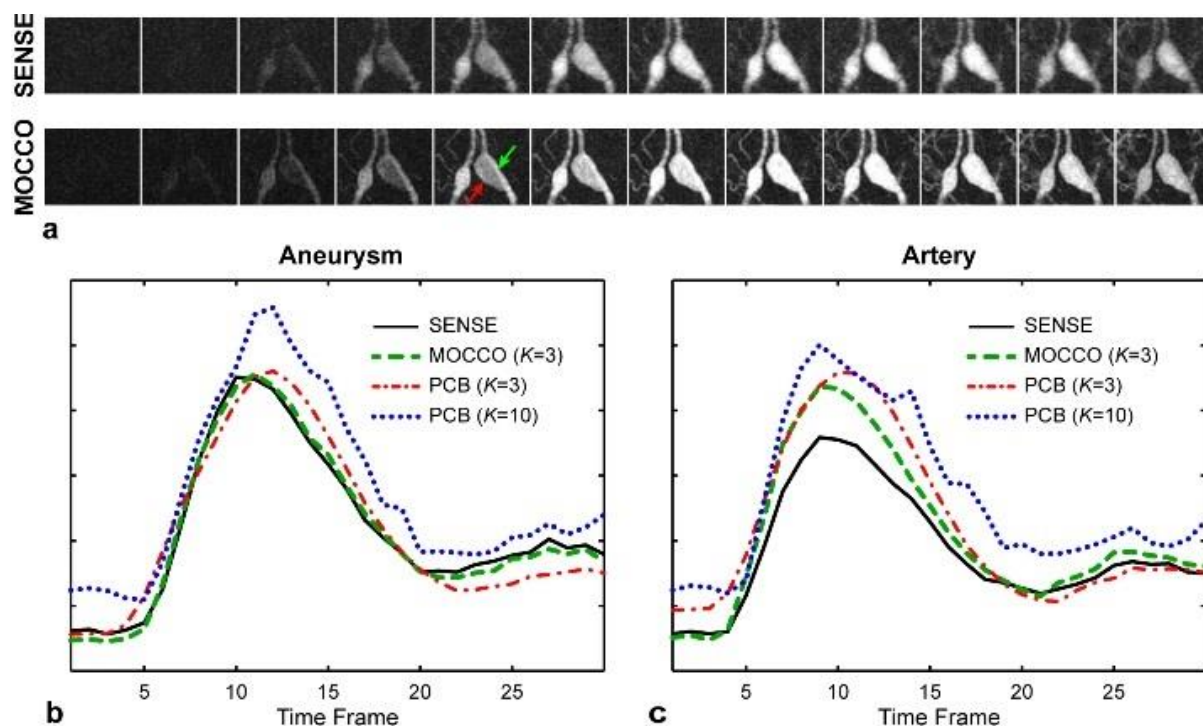


Figure 3. (a) Magnified ROI in the time series reconstructed by SENSE and MOCCO, (b, c): Contrast enhancement waveforms measured in the aneurysm and its feeding artery indicated by red and green arrows in (a), respectively.

Acknowledgement

The study was supported by Russian Science Foundation, project № 14-45-00040.

References:

- [1] Hadizadeh D R, von Falkenhausen M, Gieseke J et al. 2008 Cerebral arteriovenous malformation: Spetzler-Martin classification at subsecond-temporal-resolution four-dimensional MR angiography compared with that at DSA. *Radiol* **246** 205–213
- [2] Haider C R, Riederer S J, Borisch E A, et al. 2011 High temporal and spatial resolution 3D time-resolved contrast-enhanced magnetic resonance angiography of the hands and feet. *J. Magn. Reson. Imaging* **34** 2–12
- [3] Peters D C, Grist T M, Korosec F R, et al. 2000 Undersampled projection reconstruction applied to MR angiography. *Magn Reson Med* **43** 91–101
- [4] Meyer C H, Hu B S, Nishimura D G, Macovski A 1992 Fast spiral coronary artery imaging. *Magn Reson Med* **33** 202–213
- [5] Barger A V, Block W F, Toropov Y, et al. 2002 Time-resolved contrast-enhanced imaging with isotropic resolution and broad coverage using an undersampled 3D projection trajectory. *Magn Reson Med* **48** 297–305
- [6] Haider C R, Hu H H, Campeau N G, et al. 2008 3D high temporal and spatial resolution contrast-enhanced MR angiography of the whole brain. *Magn Reson Med* **60** 749–760
- [7] Noll D C, Nishimura D G, Macovski A 1991 Homodyne Detection in Magnetic Resonance

- Imaging, *IEEE Trans Med Imaging* **10** 154-163
- [8] Muhammad U, Batchelor P G 2009 Optimized Sampling Patterns for Practical Compressed MRI" *SAMPTA'09, International Conference on Sampling Theory and Applications*
- [9] Candès E J, Romberg J 2007 Sparsity and incoherence in compressive sampling. *Inverse Problems* **23** 969-985
- [10] Block K T, Uecker M, Frahm J 2007 Undersampled radial MRI with multiple coils. Iterative image reconstruction using a total variation constraint. *Magn Reson Med* **57(6)** 1086-1098
- [11] Lustig M, Donoho D, Pauly J M 2007 Sparse MRI: The application of compressed sensing for rapid MR imaging. *Magn Reson Med* **58(6)** 1182-1195
- [12] Adluru G, Awate S P, Tasdizen T, Whitaker R T, Dibella E V 2007 Temporally constrained reconstruction of dynamic cardiac perfusion MRI. *Magn Reson Med* **57(6)** 1027-1036
- [13] Velikina J V, Alexander A L, Samsonov A A 2013 Accelerating MR parameter mapping using sparsity-promoting regularization in parametric dimension. *Magn Reson Med* **70(5)** 1263-1273
- [14] Velikina J V, Samsonov A A Reconstruction of Dynamic Image Series from Undersampled MRI Data Using Data-Driven Model Consistency Condition (MOCCO). *Magn Reson Med*, early view
- [15] Liang Z P 2007 Spatiotemporal imaging with partially separable functions. In: *Proc of ISBI; Washington, DC, USA* 988-991
- [16] Pedersen H, Kozerke S, Ringgaard S, Nehrke K, Kim W Y 2009 k-t PCA: temporally constrained k-tBLAST reconstruction using principal component analysis. *Magn Reson Med* **62(3)** 706-716
- [17] Deoni S C L, Rutt B K, Peters T M 2003 *Magn Reson Med* **49(3)** 515-526
- [18] Pruessmann K P, Weiger M, Bornert P, Boesiger P 2001 Advances in sensitivity encoding with arbitrary k-space trajectories. *Magn Reson Med* **46(4)** 638