An Application of Regularization by Model Consistency Condition to Accelerated Contrast-Enhanced Angiography

Julia V Velikina[1], and Alexey A Samsonov[2]
[1]*Medical Physics, University of Wisconsin - Madison, Madison, Wisconsin, United States,* [2]*Radiology, University of Wisconsin - Madison*

Introduction: The clinical need for high spatial and temporal resolution in time-resolved MR applications often necessitates image reconstruction from incomplete datasets because the total scan time is limited due to contrast passage or breath hold requirements. The advent of compressed sensing (CS) [1] provided a new sub-Nyquist sampling requirement for images accepting a sparse representation in some basis. However, limited spatial sparsity of MR images affords only moderate acceleration factors (2-4) before CS reconstruction introduces image blurring / blocky artifacts. A better sparsification can be achieved by exploiting spatio-temporal correlations in the time series as shown in [2-4]. In these methods the underdetermined image reconstruction problem is regularized by making assumptions about the nature of temporal waveforms. The accuracy of reconstruction and achievable acceleration then depends on the validity of these assumptions in practice. In particular, *k-t* PCA [2] postulates that temporal behavior of different image regions can be described by a linear combination of several principal components (PCs), which are learned from low-resolution training data. *k-t* PCA was validated in cardiac perfusion imaging [2,5]. However, its utility in contrast-enhanced (CE) intracranial angiography remains to be investigated because in certain disease, e.g. intracranial aneurysms, small regions of pathological anatomy exhibit temporal behavior that is radically different from the rest of vasculature and cannot be described well by the chosen PCs. Recently, a new model-based approach (MOCCA) [6] was proposed for quantitative MRI. MOCCA relies on linearized representation of non-linear operators mapping between image space and space of MR parameters. Such linearization is obtained by applying PCA or K-SVD to compress a set of analytical curves derived from a theoretical signal model equation. MOCCA was shown to be robust to local misrepresentation of the image series behavior by the theoretical model. In this work, we modify the MOCCA technique to be applicable to CE angiography, where temporal signal behavior has to be learned from the available data due to lack of theoretical model.

Theory: Here, we restate the ideas behind MOCCA approach in the context of its adaptation to CE angiography. The temporal image series reconstruction solves the linear system $\boldsymbol{E}f = b$, where $\boldsymbol{E}$ is the encoding matrix and b is the measured *k*-space data for all time frames. In accelerated imaging, $\boldsymbol{E}$ is ill-conditioned and requires a regularization. As in [2], we assume that temporal behavior of most pixels can be approximated well by a linear combination of several waveforms. However, MOCCA allows for deviations from the chosen model as follows. Let $(\boldsymbol{w_k})$ be the set of chosen representative waveforms that span a linear subspace $\boldsymbol{W}$ of waveforms satisfying the model assumption. Let $\boldsymbol{D}$ be a synthesis operator mapping a set of coefficients (c_k) to a linear combination $\sum c_k \boldsymbol{w_k} \in \boldsymbol{W}$; and $\boldsymbol{D}^*$ be its adjoint analysis operator yielding coefficients of projection of an arbitrary waveform w onto $\boldsymbol{W}$, $\boldsymbol{D}^*: w \rightarrow (< w, \boldsymbol{w_k} >)$. If the model assumption is satisfied for a given pixel, then its temporal waveform w is "close" to $\boldsymbol{W}$, so $\boldsymbol{D}\boldsymbol{D}^* w \approx w$. Hence, reconstruction is regularized by the chosen temporal behavior model, allowing for deviations in a small number of pixels through the use of hybrid l_1/l_2 norm: $f = \arg\min_f \left(\|\boldsymbol{E}f - b\|_2^2 + \lambda \|(\boldsymbol{D}\boldsymbol{D}^* - \boldsymbol{Id})f\|_{l_1/l_2} \right)$.

Methods: The temporal behavior model is constructed from a low resolution training data f_{tr} reconstructed a fully sampled central region of *k*-space. The f_{tr} series is reformatted into a $N_x \times N_{fr}$ matrix, where N_x is the number of pixels in each low resolution image and N_{fr} is the number of time frames. An SVD decomposition is performed on this matrix to learn its PCs, of which the first three are chosen as the representative waveforms $(\boldsymbol{w_k})$. It is impractical to choose more PCs as their oscillatory nature results in noise amplification in reconstructed images. Minimization is implemented via iteratively reweighted least squares algorithm [7] with 10 reweightings. The balance between sparsity promoting properties of l_1-norm and noise optimality of l_2-norm is achieved through the use of hybrid norm $\|x\|_{l_1/l_2} = \sum_k \left(\sqrt{1 + |x_k/\sigma|^2 - 1} \right)$, with the cut-off parameter σ chosen as $0.6\mathrm{std}(x)$ in the first reweighting and gradually decreased in the subsequent ones.

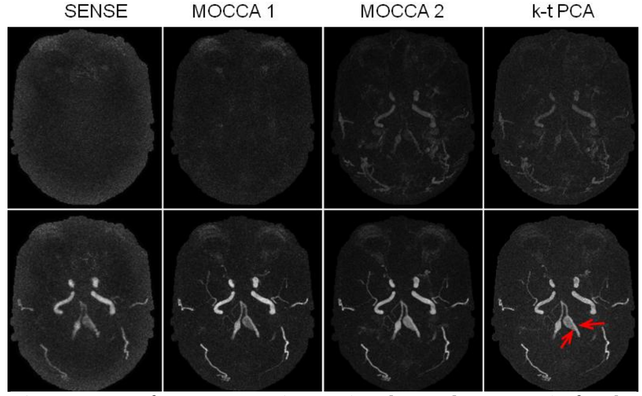

Figure 1. Time frames at 2.4 s (top row) and 7.2 s (bottom row) after the beginning of examination.

The proposed method 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 ™ 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 mm^3. The data were reconstructed from 15 radial projections per slice per 1.2 s time frame (acceleration factor R=27) using iterative SENSE [9], *k-t* PCA [2] and the proposed method with l_1/l_2-norm (MOCCA 1) and l_2-norm (MOCCA 2) in the penalty term. Reconstructed images were compared for image quality and temporal waveform fidelity.

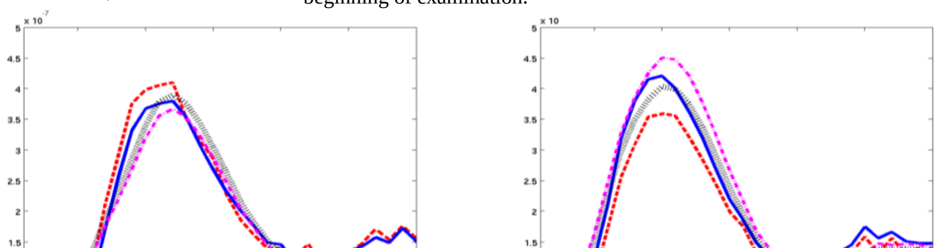

Figure 2. Waveforms of the ROIs indicated by arrows in Fig. 1 for SENSE (dashed), MOCCA 1 (solid), MOCCA 2 (dotted), k-t PCA (dash-dot).

Results: Images in Fig. 1 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 Fig. 2.

Conclusions: The presented extension of the MOCCA approach with learned temporal behavior from low-resolution dynamic images is a good fit to highly accelerated CE angiography. The modified MOCCA was shown to produce reliable results in distinguishing of different filling patterns of pathological vasculature due to the methods's robustness to model misrepresentation.

Acknowledgements: We acknowledge financial support of R01NS065034 and R01NS066982.

References: [1] Candes E et al. Inverse Problems 23:969. [2] Pedersen H et al. MRM 2009;62:706. [3] Jung H et al., MRM 2009;61:103. [4] Velikina JV et al. Proc. ISMRM 2010: 4876. [5] Vitanis V et al. MRM 2011;65:575. [6] Samsonov AA, submitted to ISMRM 2012. [7] Wohlberg B et al. IEEE SPL 2007;14:948. [8] Bube KP et al. Geophysics,1997;62:1183. [9] Pruessmann KP et al., MRM 2001;41:638.