Improved Time Series Reconstruction for Dynamic MRI

U. Sümbül[1], J. M. Santos[1], and J. M. Pauly[1]

[1]Electrical Engineering, Stanford University, Stanford, CA, United States

Introduction: Dynamic imaging reveals vital functional information on the object of interest. Such acquisitions, however, suffer from low SNR and low temporal resolution. To keep the temporal resolution at a reasonable value, longer readouts and fewer excitations are often employed, resulting in various flow and motion related artifacts. Previous works such as the UNFOLD[1], TSENSE[2] and kt-BLAST[3] work better on a Cartesian grid, thereby not taking advantage of the more desirable flow and motion characteristics of various non-Cartesian trajectories. We propose an algorithm addressing these shortcomings. It shares the same statistical flavor as kt-BLAST. We demonstrate 4x increase in the frame rate with better SNR and temporal response and a very short reconstruction time(essentially 2 gridding and 2 Fourier transform operations per frame) using spiral trajectories. We compare our algorithm with the sliding window reconstruction, which also provides a rapid reconstruction.

Theory: We model the temporal variation of the heart with the following dynamic system [4]:

$$S_n = S_{n-1} + U_n, \qquad X_n = \mathbf{G_n}\, \mathbf{F}\, \mathbf{\Gamma}\, S_n + W_n.$$

Here, S_n represents the true image at time n, and $\mathbf{G_n}$, $\mathbf{F}$ and $\mathbf{\Gamma}$ denote the time-dependent gridding operator, the Fourier transform operator and deapodization operator, respectively. U_n is the change in the image from time n-1 to n, and W_n is the observation noise with a covariance of $\Sigma=\sigma^2 I$. X_n denotes the raw data used for the n^{th} frame. The quality of the reconstructions particularly depends on accurately characterizing the difference process U_n. We employ the Kalman filter[5] on this model by sending one-fourth of the full data set for each frame and expecting the Kalman filter to resolve the resulting aliasings.

Methods: The RTHawk real-time system[6] is used with both GRE and SSFP pulse sequences and in-vivo cardiac data is acquired by a single surface coil(3" coil for SSFP and 5" coil for GRE). Display FOV is 20 cm with a resolution of 2 mm. No ECG-gating or breath-holding was used. Short scans of 10 seconds are used to estimate the necessary statistics. A small region around the center of the k-space(1% of total k-space) is fully sampled for each frame and is not sent to the Kalman filter. Since image correlations are mostly due to the very low spatial frequency content, the outer region will exhibit much reduced cross-correlations between pixels. Therefore, the time consuming matrix inversion of the Kalman filter becomes the easy task of inverting diagonal matrices by ignoring any residual cross-correlations. The inner trajectory is kept constant for all frames to get rid of flickering artifacts due to the rotation of residual aliasings, whereas the undersampled outer trajectory is rotated for each frame to cover the k-space. The outer part uses a linearly decreasing density spiral for SNR efficiency. *Fig. 1* depicts a simplified system view of the reconstruction.

Results: The left column of *Fig. 2* shows 4 consecutive frames obtained by sliding window reconstruction, and the right column shows the corresponding frames obtained by Kalman filtering.(GRE excitation) The time between consecutive rows is 33.7ms.(~ 30 fps) In the left column, the sliding window is used only for the undersampled region for a fairer comparison. The right column has better SNR, as demonstrated by the reduced noise and the sharper structures in the background. More importantly, the Kalman reconstruction is much more responsive to the rapid valvular motion. Especially in the third row, the left frame is blurred by motion whereas the right frame maintains a sharp depiction of the valve.(arrows) *Fig. 3* shows three consecutive frames from a similar experiment except that an SSFP pulse sequence is used. The top row shows the sliding window reconstruction and the bottom row shows the Kalman reconstruction. Due to practical limitations in the real-time system, there is a dead time in each TR, resulting in reconstructions running at 16 fps. Yet, the merit of the proposed algorithm is still demonstrated by the reconstructions.

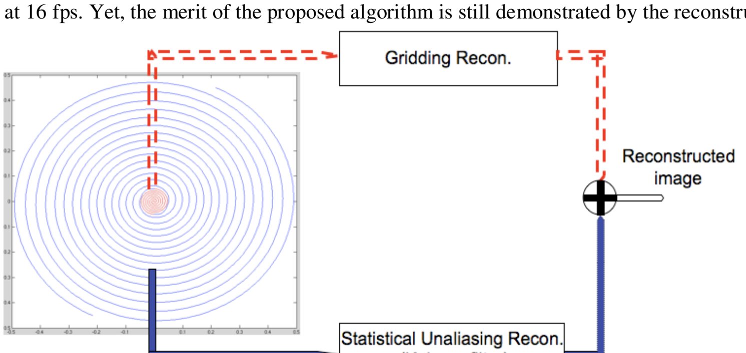

Figure 1 – A simplified view: The very center of the k-space is reconstructed conventionally and the remaining part is fed to the Kalman filter. These reconstructions are then combined by simple summation. The two trajectories(in-out) are connected in a time-optimal manner.

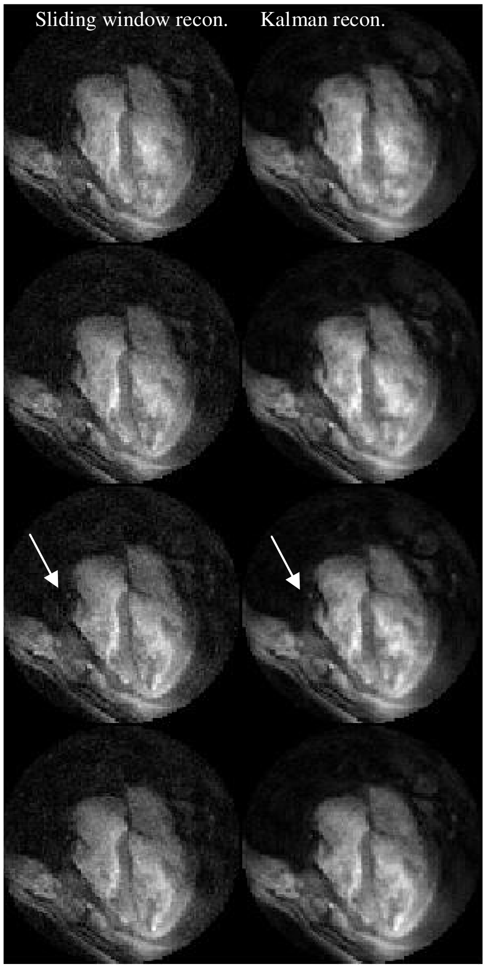

Figure 2 – Four consecutive frames from a cardiac experiment – Left column: Sliding window recon. Right column: Kalman recon. 8-interleaf GRE experiment, every 2 of 8 are input to the Kalman filter for a 4x recon.

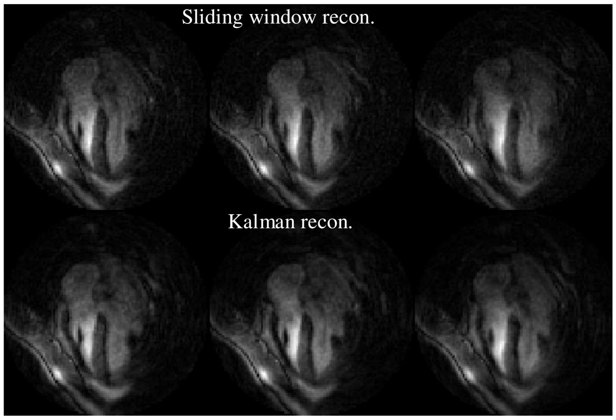

Figure 3– Three consecutive frames from a cardiac experiment – Top row: Sliding window recon. Bottom row: Kalman recon. 48-interleaf SSFP experiment, every 12 of 48 are input to the Kalman filter for a 4x recon.

Conclusions: We demonstrated that the proposed technique is very responsive to changes in time-series data. Moreover, built-in denoising capability of the Kalman filter reduces the acquisition noise. Experiments show that the proposed technique allows for better tracking of fast moving structures, in particular the cardiac valves.

References: **[1]** Madore B, et al., Magn Reson Med, 42:813 – 828, 1999 **[2]** Kellman P, et al., Magn Reson Med, 45:846 – 852, 2001 **[3]** Tsao J, et al., Magn Reson Med, 50:1031-1042, 2003 **[4]** Sümbül U, et al., 15th ISMRM, 302, 2007 **[5]** Chui CK, Chen G, Kalman Filtering with Real-Time App, Springer-Verlag, 1987 **[6]** Santos J, et al., IEEE EMBS 26th, 1048, 2004 2003

Acknowledgments: This work is supported by NIH grant R01HL074332.