Kalman Filter Techniques for Accelerated Cartesian Dynamic Cardiac Imaging

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Introduction: In dynamic MRI, spatial and temporal parallelism are exploited to reduce scan time. Real-time reconstruction is sometimes necessary for timely feedback during the scan. The commonly used view sharing techniques suffer from reduced temporal resolution and many of the more advanced reconstruction methods, including the newly developed methods based on compressed sensing, are either retrospective or time-consuming, or both. The goal of this study is to use a Kalman filter model suitable for real-time reconstruction to increase the temporal resolution in the dynamic MRI reconstruction. The original application of Kalman filter to dynamic MRI was limited to non-Cartesian trajectories [1], because of an assumption made in the model to make the computation feasible. In this abstract we overcome this limitation and apply the model to the more commonly used Cartesian trajectories. Furthermore, we combine the Kalman model with parallel imaging techniques including SENSE and TGRAPPA to further increase the spatial and temporal resolution and SNR.

Theory: The basic Kalman filter model is given in Eq. 1, where the image $\underline{x}_k$ and the corresponding undersampled k-space measurement $\underline{z}_k$ are vectors. However, the dimension of the vectors is a major obstacle in the implementation of this model,

$$\begin{aligned} \underline{x}_k &= \underline{x}_{k-1} + \underline{w}_{k-1}, \quad && \underline{w}_k \sim N(\underline{0}, Q_k) \\ \underline{z}_k &= F_k \underline{x}_k + \underline{v}_k, \quad && \underline{v}_k \sim N(\underline{0}, R_k) \end{aligned} \qquad \text{Eq.1}$$

because the relevant matrices are too large to directly compute. In [1], the diagonalization assumption of $F_k^T F_k$ is adopted to simplify the calculation into a pixel-by-pixel process. This assumption is not valid for Cartesian trajectories, because the aliasing pattern is very conspicuous and the off-diagonal term is significant. However, for 2D Cartesian imaging, undersampling only happens along the phase encoding direction; therefore, we can do a Fourier transform along the readout direction first and apply the Kalman filter model along the phase encoding direction for each readout pixel to simplify the model into a 1D problem. With this simplification, the direct implementation of Kalman filter becomes feasible with appropriate estimations of Q_k, R_k and the initial conditions. For non-gated real-time cardiac imaging, Q_k and R_k are assumed to be constant since the statistical properties for this dynamic process can be regarded as time-invariant; therefore, we can pre-calculate the Kalman gain matrix K_k for each step and the calculation required as the measurement proceeds is just matrix-vector multiplication and real-time reconstruction is feasible.

If multiple receiver coils are available, we can easily combine the Kalman filter model with SENSE by incorporating coil sensitivity information into the model by replacing F_k with $F_k S_{ik}$ and include data from all of the coils in the measurement vector. However, since it is difficult to accurately estimate coil sensitivity in dynamic MRI, we also developed a combination of the Kalman filter model with TGRAPPA [2] by first filling the missing k-space lines with TGRAPPA for each coil. We then used the resulting k-space data as $\underline{z}_k$ and replaced F_k with the fully sampled Fourier matrix. This method requires a modified measurement error covariance matrix R_k to reflect the fact that the k-space data estimated using TGRAPPA is not as reliable as the measured k-space data. Finally, the coil images are combined to get the final image series. This results in an effective combination of TGRAPPA with the Kalman filter.

Methods: To study the effects of the Kalman filter model in reconstruction of undersampled data, we first conducted a series of simulations comparing dynamic images reconstructed from subsampled k-space data to the original fully-sampled images. We compared the following techniques: sliding window (SW), SLAM (using a triangle window for interpolation between neighboring frames to fill the unacquired k-space) [3], kt-FOCUSS [4] and Kalman filter. Also we performed non-gated real-time cardiac imaging experiments with a 2D Cartesian bSSFP sequence on a Siemens Avanto 1.5T scanner equipped with the 32-channel body coil. A training scan of about 2.5s was required before data acquisition for the parameter estimation. The total scan time was about 10s and the acceleration factor was 4-6. Array compression was used to accelerate the reconstruction speed. A blind review focused on temporal resolution and spatial unaliasing was performed by two experienced cardiologists to compare SW, SLAM, TGRAPPA, Kalman filter combined with SENSE (KF-SENSE), and Kalman filter combined with TGRAPPA (KF-TG).

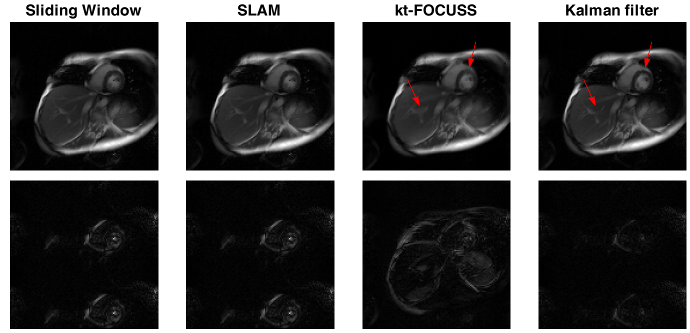

Figure 1. Images reconstructed using sliding window, SLAM, kt-FOCUSS and Kalman filter (top row) and the corresponding difference images (bottom row).

Results: Figure 1 shows the images reconstructed using sliding window, SLAM, kt-FOCUSS and Kalman filter, and the corresponding difference images with the fully sampled image in a 2x single-coil simulation with a free-breathing non-gated cardiac image series. The Kalman filter model gives a better reconstruction as the difference is reduced compared with sliding window and SLAM. The appearance of the aliasing pattern is similar for these three linear reconstructions, although the magnitude changes. The appearance of the aliasing pattern in the regions near the arrows is substantially different for kt-FOCUSS, probably because it is a nonlinear reconstruction. Figure 2 shows the statistical results from the blind review of 16 dynamic short-axis cardiac image sets with multiple coils. It is shown that the temporal resolution for KF-SENSE and KF-TG are significantly improved ($p<0.05$) compared with the sliding window (SW) and SLAM, and the spatial aliasing is reduced compared with TGRAPPA alone. Comparing KF-SENSE with KF-TG, the former behaves slightly better in spatial unaliasing and the latter behaves better ($p<0.05$) in temporal resolution. The reconstruction speed for KF-TG is much higher than KF-SENSE, because the Kalman gain matrix in KF-TG can be pre-calculated. All matrices are available before the measurement for KF-TG, but the dynamic coil sensitivity in the KF-SENSE model cannot be pre-estimated.

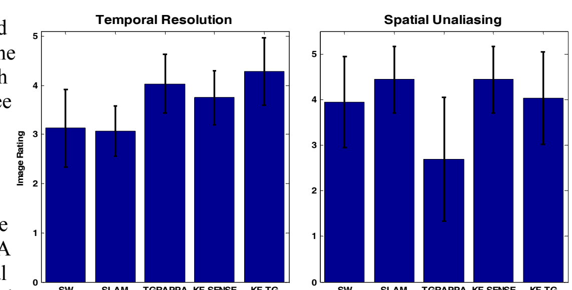

Figure 2. Temporal resolution and spatial unaliasing ratings for short axis experiments (5 = best).

Conclusions: In this abstract we have presented a Kalman filter model based reconstruction method for Cartesian trajectories that is suitable for real-time reconstruction and maintains linearity in the reconstruction process. We also combined this model with SENSE and TGRAPPA to further increase the temporal and spatial resolution. Superiority over SW and SLAM in temporal resolution and TGRAPPA in spatial unaliasing has been demonstrated by a blind review. The Kalman filter model is not limited to cardiac MRI and can be easily extended, since the 1D simplification makes it straightforward to adapt the Kalman filter for dynamic MRI.

References: [1] Sümbül, et al. IEEE Trans Med Imaging 28:1093-1104 2009. [2] Breuer, et al. MRM 53:981-985 2005. [3] Rehwald et al. Radiology 220:813-828 2001. [4] Jung et al. MRM 51:103-116 2009.

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