High Frame Rate Cardiac Imaging Using Kalman Filtering

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

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

Introduction: Dynamic cardiac imaging is essential when the actual cardiac motion is desired as a streaming video rather than a two-dimensional still image. From a diagnostic perspective, it is of utmost importance to obtain as high a frame rate as possible so as to correctly monitor the heart and not miss any anomalies. However, current real-time imaging methods can only provide modest frame rates due to various physical constraints on the acquisition. We have developed an imaging method that allows us to reconstruct videos at roughly twice the frame rate by exploiting temporal correlations. We employ a Kalman filter, which is known to be mean-square optimal when the noise processes are Gaussian. Our method is suitable for real-time applications due to its simple reconstruction algorithm and of particular importance is that it does not interfere with other common intra- and inter-frame speed-up techniques such as parallel imaging, and sliding window reconstruction. Hence, it can be used together with those methods. Moreover, the reconstruction time is a weak function of the number of k-space samples.

Methods: Natural videos exhibit high temporal correlations, encouraging us to devise methods exploiting this redundancy. We use the RTHawk real-time system [1] for imaging. This system provides the necessary infrastructure for real-time acquisition, control and reconstruction. Various slices through the heart, some of which involve valves, are monitored in different experiments. We use a constant-density spiral acquisition, requiring 4 interleaves of duration 21.6 ms to achieve a 2 mm resolution over an FOV of 20 cm and the corresponding reconstruction runs at 23.2 frames per second (fps). The k-space trajectory is depicted in Figure 1. Each spiral extends beyond the origin to sample the low frequency region of its conjugate spiral. After acquisition, the missing parts are estimated to yield one frame per two spirals. Thus, it takes 21.6ms x 2 = 43.2 ms to acquire one frame. In our particular experiment, each spiral has 3048 samples, 400 of which actually belong to its conjugate counterpart.

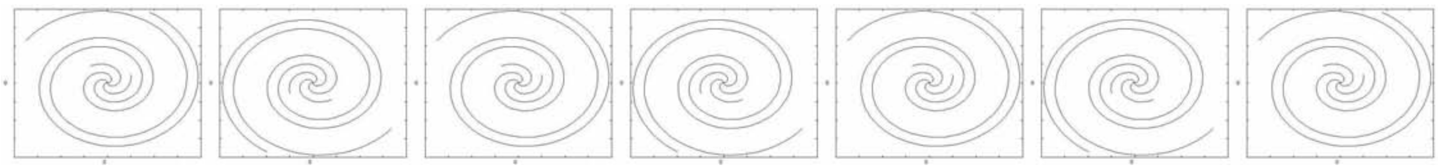

Figure 1: k-space acquisition protocol: Spirals extend beyond the origin and each conventional spiral is fully sampled on alternating frames.

To estimate the missing parts, we use Kalman filtering. The Kalman filter is especially efficient in real-time tracking problems and it gives a precise solution to causal filtering of a process based on a finite number of measurements and without assuming stationarity. [2] We also employ the fact that the temporal variation of one k-space sample is correlated to the temporal variation of other k-space samples. In our reconstruction, we treat each spiral independently and thus we actually run 4 separate Kalman filters, one for each spiral. Note that by design, every spiral is fully sampled on alternating frames. We want to estimate the missing part of a spiral using past and future states of that spiral by looking at how the low-frequency part of the spiral, which is sampled on each frame, behaves temporally. Ideally, we want to use the k-space data itself as the state vector in the Kalman scheme. However, due to the overwhelming number of samples, this approach is not suitable for our purposes. Instead, we first solve a least-squares problem on the low-frequency components to find a set of rough coefficients. These coefficients are then fed into the Kalman filter to yield the ultimate coefficients used in the weighted sum reconstruction over the fully sampled spirals at different temporal positions. Hence, the state vector *x* in our Kalman scheme is a vector of coefficients. This way, our method becomes very suitable for real-time applications. To estimate missing parts of frame F, frames F+1, F+3,… and F-1, F-3,… are used. In this particular reconstruction, we used 5 frames from the future and 10 frames from the past so that approximately one full heart cycle is covered. As for the Kalman scheme, we chose a zeroth-order tracking model to further simplify the process. (Figure 2.) The Kalman filter evolves on the data by using certain mean and variance estimates, which are needed to initialize the filter. Thus, to obtain these estimates, we first run a pre-scan of a few seconds long before the actual data acquisition. This is performed online by just pushing a button.

$$\begin{aligned} x[n+1] &= x[n] + v[n] \\ y[n] &= x[n] + w[n] \end{aligned}$$

Figure 2: x[n] is the state vector and y[n] is the observation, which is the solution to the least-squares problem. v[n] and w[n] are noise processes.

Results: The left image of Fig. 3 shows a snapshot from the short axis video of a healthy volunteer's heart. The right image shows a snapshot from the four-chamber view video of the same volunteer's heart.

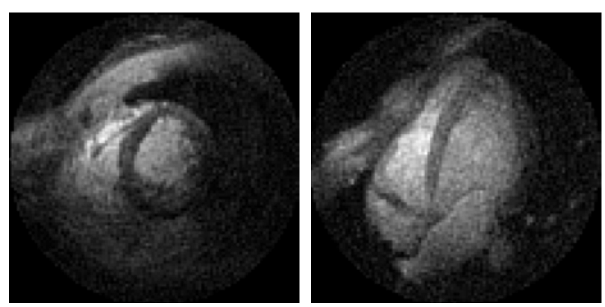

Figure 3: Two snapshots from different experiments, running at 23.2 fps

Conclusions: Dynamic cardiac imaging requires a high frame rate. Our method exploits the temporal correlations in cardiac videos to double the frame rate. Given this basic method, even higher frame rates and/or higher quality reconstructions can be achieved by both modifying this method and incorporating this method into already existing intra- and inter-frame speed-up techniques.

References:

[1] Santos J, et al., IEEE EMBS 26th, 1048, 2004. [2] C. K. Chui, G. Chen, Kalman Filtering with Real-Time Applications, Springer-Verlag, 1987