# Optimization of Variable-Density Cartesian Sampling for Time-Resolved Imaging

**R. F. Busse[1], K. Wang[2], J. H. Holmes[1], J. H. Brittain[1], and F. R. Korosec[3]**

[1]Applied Science Laboratory, GE Healthcare, Madison, WI, United States, [2]Medical Physics, University of Wisconsin, Madison, WI, United States, [3]Radiology, University of Wisconsin, Madison, WI, United States

**Introduction:** In time-resolved MR imaging, only a limited number of projections or phase encodes can be acquired at the desired temporal resolution. To improve temporal and/or spatial resolution, the center of k-space may be sampled at a higher rate than the periphery (1-4), thus sampling k-t space with variable density. For example, the k-t density for TRICKS (3) is a "top hat" function with 1 near the center and 1/N in the periphery, where N frames are required to sample all points. Dynamic radial acquisitions (5) also sample k-t space with variable density, proportional to $1/k_r$ (for 2D). For Cartesian (3,4) or non-Cartesian (6) acquisitions, a filter may be applied to select or weight k-t data samples closest to the nominal time of each reconstructed frame. Any changes to an imaged object that occur within the span of time over which data is used in the reconstruction cause errors, most notably incorrect position and/or intensity of the object and artifacts that may appear beyond the boundary of the object. Here we examined several different variable k-t density Cartesian sampling patterns to determine what effect they have on time-resolved imaging, in particular with respect to temporal fidelity and spatial artifact distribution.

**Methods:** Three variable density 3DFT acquisition patterns were considered, as shown in the left column of Figure 1. (These examples use a 256×256 $k_y$-$k_z$ grid with 51500 views total, 6600 acquired per time frame.) *Variant A* used a "top-hat" density function, acquiring the center of k-space every frame and the periphery in radial sectors, as proposed in ref. (4). *Variant B* used a density function proportional to $1/k_r$ (capped at 1 in the center and dropping to 1/N at the edge) and grouped views along radial lines. *Variant C* also used a $1/k_r$ density function, but interleaved samples on a point-wise basis. All variants used the same number of views per time frame, but Variants B and C, with $1/k_r$ density, required more frames than Variant A to sample the complete set of k-space points (N=15 vs. 9 in this example). Sequential (e.g. contiguous sector) and bit reverse ordering of the N sampling patterns was modeled for analysis. The step response of the system was analyzed by modeling the instantaneous arrival of contrast in vessels of various sizes perpendicular to the y-z plane. Acquisition was simulated and reconstruction performed using nearest temporal neighbor interpolation to fill missing views. The "temporal footprint" was calculated as the temporal derivative of the signal enhancement curve. "Temporal blur" was defined as the standard deviation of the temporal footprint, centered at the time of peak signal change.

**Results:** The third and fourth columns of Figure 1 show a reconstructed frame, immediately after simulated contrast arrival, of an object with 3×3 pixel cross section. The central ¼ of the 256×256 image is displayed and the blue-to-red color map (identical for all cases) was windowed to visualize the artifact pattern in the y-z plane. Artifacts were observed to be more dispersed when using bit reversed ordering and when interleaving the samples by point rather than grouping views radially. Figure 2 shows the signal level within the object as a function of time (top), and the derivative of this curve (bottom) – the temporal footprint. The $1/k_r$-density variants with sequential ordering *increased* temporal blur compared to the top-hat-density variant, however with bit reverse ordering, $1/k_r$-density *decreased* temporal blur, despite incorporating data over a longer period. For the top-hat density variant, bit reverse ordering had no effect on temporal blur. The footprint shape and standard deviation were object dependent, growing more compact with increased object size, but the trends were the same for all but a point object in which case variable k-t density (both top-hat and $1/k_r$) provides no advantage since all k-space locations have equal energy.

**Discussion**: These modeling studies indicate that reconstruction errors in temporally resolved imaging – both temporal blur and coherent artifacts – can be reduced by employing a continuously variable k-t density sampling pattern and interleaving the samples in k-t-space on a point-wise basis. While these studies used sampling patterns that met the Nyquist criterion over the N frames, this is not a requirement since under-sampling artifacts are well dispersed. Adding parallel imaging and/or partial-Fourier would significantly reduce the views required and enable greater acceleration (7). Additionally, reconstruction techniques other than temporal nearest neighbor, such as MART (8) or HYPR (9), which benefit from well dispersed under-sampling artifacts in the time frames, may be used, as described in a separate study.

References: [1] van Vaals, JMRI 3:671 (1993) [2] Doyle, MRM 33:163 (1995) [3] Korosec, MRM 36:345 (1996) [4] Madhuranthakam, MRM 51:568 (2004) [5] Rasche, MRM 34:754 (1995) [6] Liu IEEE TMI 25:148 (2006) [7] Haider, MRM 60:749 (2008) [8] Gordon, J Theor Biol, 29:471 (1970) [9] Mistretta, MRM, 55:30 (2006)

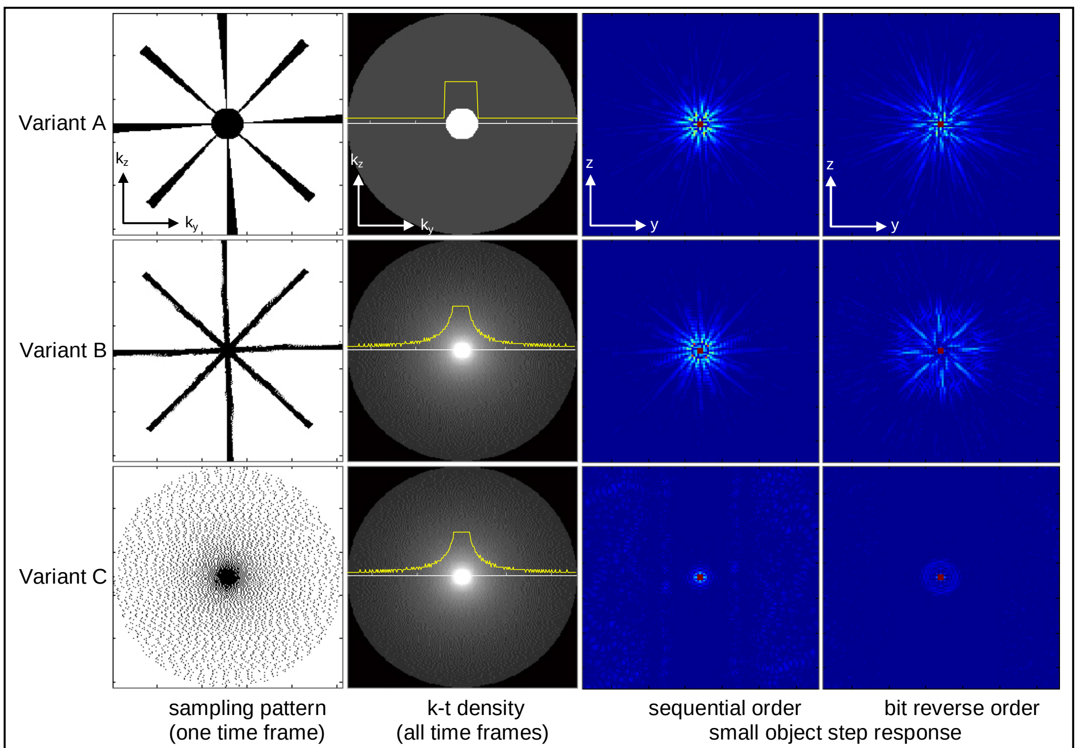


**Figure 1**

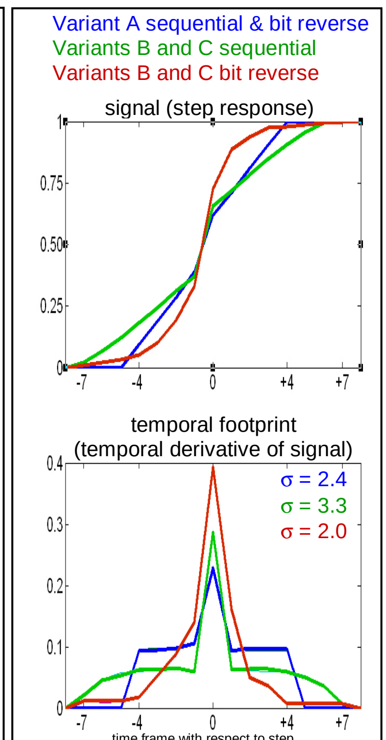


**Figure 2**