

High Spatial Frequencies Are More Dynamic Than Low Spatial Frequencies In Cardiac Motion

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Introduction

Effective strategies for sparse sampling of kt -space are important for fast dynamic imaging. Following observations in early landmark papers [1-3] the temporal sampling rate of each k -space view is often linked to the signal energy represented by that view in k -space for a certain class of images, in general considering only the spatial or spatiotemporal spectrum of the entire image. Based on resulting criteria, sparse sampling schemes typically sample low spatial frequencies more frequently than high spatial frequencies, implicitly considering signal-to-noise ratio SNR as the dominant factor in image quality [1-4]. For cardiac imaging this concept is represented by the BRISK formalism [2]. Sampling schemes for angiography and dynamic lesion enhancement imaging were established by TRICKS [3] and STBB [4].

In this work we have studied analysis of temporal spectral content as a function of the k -space frequency, illustrated with simulated and actual ciné cardiac imaging data. Dynamic spectral content was observed both globally in the image, and spatially-selectively in relevant portions of the image.

Materials and Methods

Synthetic kt -space data on a rectilinear grid were analyzed for a simulation phantom [5] with 256 phase encoding views and 16 time samples, simulating different types of cyclic motion. Types of motion (see Fig 1a), included myocardial contraction (1), sinusoidal translational motion patterns (2,3), and sinusoidal (4) and single-flash intensity (5) variation in a static object (details in [5]). Temporal spectra of each k -space view were generated by temporal DFT, for all types of motion combined, and for each type of motion individually. To this end, spectral energy coefficients $W_{k\omega}$ were generated by temporal DFT, followed by complex-conjugate multiplication. Consequently, for a sequence of 16 frames we obtained 9 coefficients for each k -space view ($W_{k,\omega=0}, \dots, W_{k,\omega=8}$), where $\omega=0$ represents static image content, $\omega=1$ contains temporal base frequency information, etc. A single temporal spectral index ξ_k was calculated to quantify the dynamics for each k , disqualifying dominant static content at $\omega=0$:

$$\xi_k = \left(\sum_{\omega=1}^8 \omega W_{k,\omega} \right) / \left(\sum_{\omega=1}^8 W_{k,\omega} \right)$$

This coefficient quantifies the mean temporal frequency observed in the dynamics each k -space view. For each type of motion a corresponding real MRI image sequence was selected and isolated from other image content by blanking all pixels outside a region of interest which contained the moving object.

Results

We consistently observed higher temporal frequency content at high spatial frequencies than at low spatial frequencies for all types of image dynamics involving object motion. This is illustrated in Figure 1 for myocardial contraction motion in the phantom image (a-c) and a short-axis scan (d-f), showing a frame from each sequence, and spectral k -space maps at low ($\omega=1$) and high ($\omega=7$) temporal frequencies. Quantitative confirmation is shown by spectral coefficients ξ_k in Figure 2 for these same images, which are consistently higher for high k_y . Exceptions were dynamics without motion i.e., limited to intensity changes of static objects: sinusoidal intensity variation showed, trivially, only spectral content at the temporal base frequency, and single-frame intensity flash dynamics resulted, also as expected, in flat spectral response across all temporal frequencies.

Discussion and Conclusions

The results of this analysis suggest that high spatial frequency spectral content, well-known to define sharp edges and other fine image details, is “more dynamic” than low spatial frequency content, known to represent the bulk of the image contrast, for dynamic imaging involving object motion. A possible explanation of this finding may be the idea that motion of an object is represented in k -space by coherent phase changes, which are greater for higher frequencies. As a result the relative differences in k -space views between time samples are also greater for high spatial frequencies, and are therefore expressed by higher frequency content in the temporal spectra of these views.

These results, in a paradox with earlier work, appear to provide grounds to reconsider sampling strategies and image quality criteria for sparse sampling in dynamic imaging involving object motion, in favor of more frequent sampling of high spatial frequencies. Since signal energy is, as shown in earlier studies, lower at high frequencies, such an approach may not be reflected by improved over-all SNR. However, it may result in more faithful edge definition, important in some applications. Even though in the present study the spectral analyses were only performed for cyclic cardiac motion, these results may extend to dynamic angiography, where edge detail is of critical importance, and possibly other non-cyclic dynamics.

References

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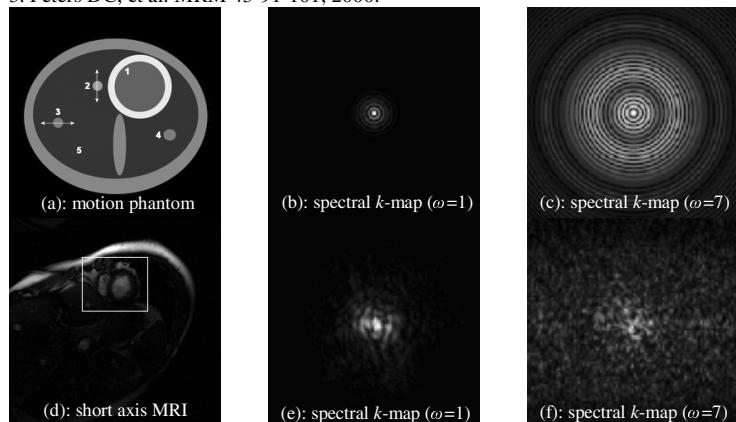


Figure 1: Image frames (a,b) and temporal spectral components (b,c; e,f) (contraction motion only)

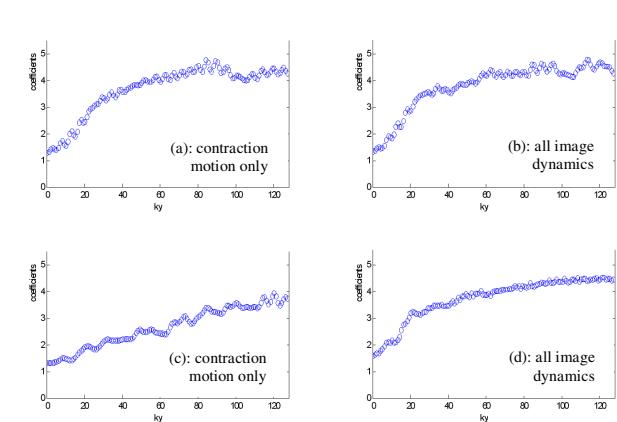


Figure 2: Spectral coefficients $\xi(k_y)$ [$k_y=0$ on left] (a,b) phantom; (c,d) MRI