Imaging Reconstruction – Exploiting Spatiotemporal Correlations for Dynamic Imaging

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Goal

This lecture aims to give an overview of various dynamic imaging methods that take advantage of spatiotemporal correlations for improved performance (e.g. higher frame rate, shorter scan duration).

What are spatiotemporal correlations?

Strictly speaking, in statistical terms, a correlation refers to the linear relationship between two variables. For example, if Y is plotted against X, and the points fall on a line, then X and Y are correlated (Fig. 1). Extending to higher dimensions, if X and Y are vectors, the presence of a correlation means that Y can be predicted from X through a linear transformation.

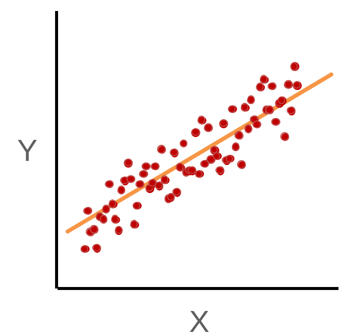

Fig. 1. Example of correlation. Y is correlated with X.

In the MRI field, the term "spatiotemporal correlations" is often used more loosely. Generally, it means that by knowing some data points (e.g. some pixels, or *k*-space points), we can determine the value of other data points that may be at different spatial locations, different *k*-space positions and/or different time points. The simple, linear relationship remains important, because many important reconstruction algorithms are linear or approximately linear.

Why are spatiotemporal correlations important?

Spatiotemporal correlations are important because one can estimate Y based on measuring X only. For example, Y may represent some unacquired data, while X represents the acquired data. By taking advantage of the correlation, one can fill in the missing data based on the acquired data. As a result, it is feasible to acquire only a fraction of the data, and accelerate the scan considerably. This concept becomes even more important in dynamic imaging because of the high degree of redundancy that is typically observed in a time series of images. As a result, there exists a great potential for accelerating a dynamic scan by measuring just a small fraction of the data and estimating the rest.

How to fill in missing data?

To take advantage of the inherent spatiotemporal correlations, the first requirement is to determine those correlations. Over the years, there have been many approaches trying to estimate them, starting from empirical approaches such as plugging in the closest data points to more sophisticated approaches (e.g.

interpolation, kriging, etc.). The key advance in the past decade in this area has been the shift from heuristic approaches to those that are more adaptive or tailored to the actual images.

What data to acquire and what to skip?

It is useful to introduce the concept of *k-t* space to help us gain a better handle of which data are acquired and which are skipped. In dynamic MRI, the raw data are acquired in *k*-space at different time points *t*. Equivalently, the raw data can be viewed as being acquired in a higher dimensional *k-t* space (1). The *k-t* sampling pattern describes the order in which data points are acquired at each time frame. These data points can refer to phase-encode lines for Cartesian sampling, projection angles for radial sampling, arcs for spiral, etc. The concept is applicable to 3D imaging as well, but is illustrated in Fig. 2 for 2D imaging for simplicity.

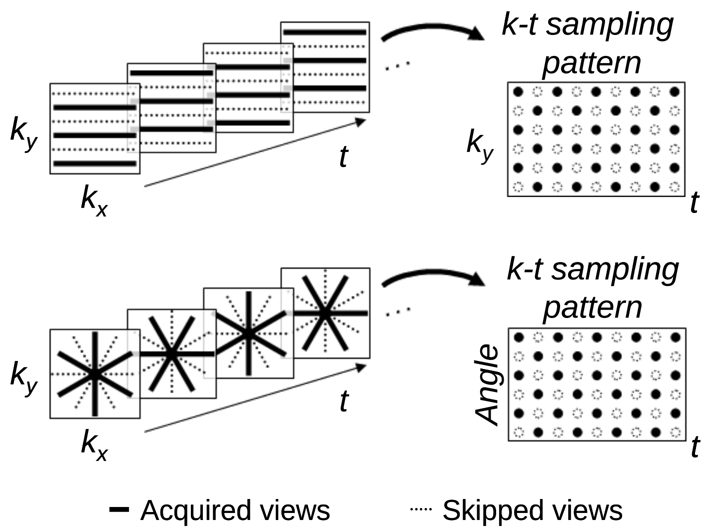

Fig. 2. (left) Examples of *k*-space trajectories at successive time frames, for Cartesian (top) and radial sampling (bottom). Solid and dotted lines indicate acquired and missing data, respectively. The arrangement of these trajectories over time can be represented schematically as a *k-t* sampling pattern (right), which illustrates which phase encode lines (or projection angles, or spiral arcs) are acquired at each time frame *t*.

Many of the reconstruction methods can be divided broadly into two classes: 1. methods with heuristically chosen *k-t* sampling patterns; 2. methods with *k-t* sampling patterns based on implicit knowledge or assumptions about the object.

Class 1: Methods with heuristically chosen *k-t* sampling pattern

This class includes methods such as sliding window (2), keyhole (3,4), RIGR (5), BRISK (6), CURE (7), TRICKS (8), undersampled radial (9), VIPR (10), golden-angle radial (11), among others.

Fig. 3 shows the *k-t* sampling pattern for these methods. There is a wide spectrum of heuristic approaches to choose the *k-t* sampling pattern. On one end of this spectrum, all parts of *k*-space are covered as evenly as possible (2) (or at least evenly on average (7)). In that case, the entire *k*-space is guaranteed to be refreshed at some average rate. On the opposite end of the spectrum, the idea is to acquire the outer parts of *k*-space at least once, but focus most of the time updating the central parts of *k*-space only, since most of the signal energy is concentrated there (3-5). The in-between approaches update different parts of *k*-space at variable rates, with more frequent updates at the center to capture the higher signal energy (6,8). All undersampled radial methods are included in this in-between approach, since radial spokes converge at the *k*-space center, so these radial trajectories naturally sample *k*-space at a variable rate.

Once the data are acquired according to the prescribed *k-t* sampling pattern, the images are reconstructed by recovering the missing data points based on the available ones. One can use a variety of interpolation and extrapolation techniques for this purpose. e.g. nearest-neighbor, linear, cubic spline interpolation, etc. One could also apply model-based approaches to estimate the missing data using the acquired data from the same time frame (5,12).

Regardless of the exact method to recover the missing data, the performance of this class of methods follows a similar behavior. In general, it is increasingly difficult to recover a data point accurately if it is far from other acquired data points. Also, interpolation is more accurate than extrapolation. Thus, methods that have demonstrated better performance tend to disperse the data samples throughout *k-t* space with increased emphasis on the *k*-space center.

Class 2: methods with k-t sampling pattern based on implicit knowledge or assumptions about the object

The second class of methods uses specific *k-t* sampling patterns that are chosen based on knowledge or assumptions about the object. In some cases, this knowledge or these assumptions are also used to aid the reconstruction. These methods include the motion-ghost method (13), reduced field-of-view method (14), DIME (15), UNFOLD (16), TSENSE (17), *k-t* BLAST (18,19), *k-t* SENSE (18,19), *k-t* GRAPPA (20), *x-f* choice (21), lattice-permuted radial (22), among others.

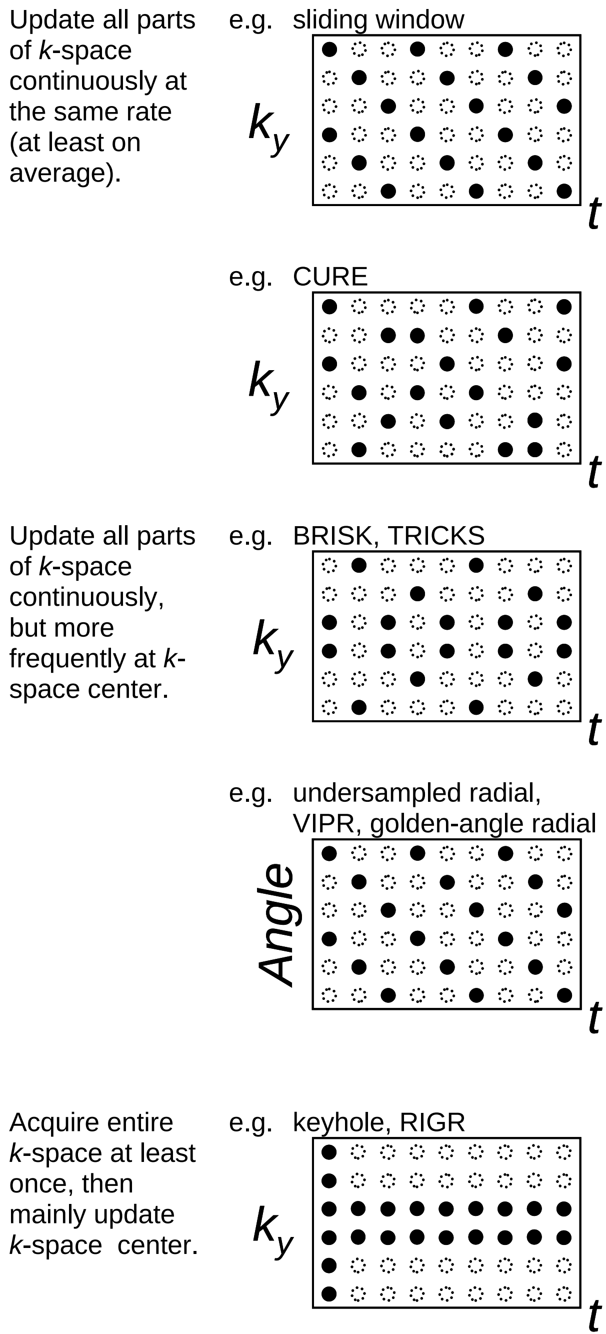

Fig.3. Heuristically chosen *k-t* sampling patterns.

According to the properties of the Fourier transform, if certain data samples are missing, the signals in the conjugate domain are contaminated through a convolution with a point spread function. In turn, the point spread function is related to the sampling pattern through the Fourier transform. For example, it is well known that if the edges of *k*-space are missing, the point spread function has a broad sinc shape, resulting in an image with a low spatial resolution. Similarly, if lines of *k*-space are skipped at even intervals (e.g. in the case of parallel imaging), the point spread function is a set of closely spaced sinc shapes, which results in aliasing in the image domain.

Extending the concept of sampling from *k*-space to *k-t* space, these properties of the Fourier transform apply in the same fashion. The signals in the conjugate domain, which is called *x-f* space (*x* = spatial axis, *f* = temporal frequency), are contaminated through a convolution with a point spread function (Fig. 4).

With this class of methods, a potential advantage is that if the signal distribution in *x-f* space is known or can be estimated, it is possible to adjust the *k-t* sampling pattern in order to control the *x-f* point spread function and minimize the amount of signal contamination. Under certain conditions, it is possible to perfectly recover the missing data.

In general, since the data acquisition and reconstruction are based on assumptions or knowledge of the signal distribution, reconstruction accuracy is dependent on the quality of those assumptions or knowledge. Depending on the implementation, the existing methods differ considerably in their robustness against practical nonidealities, such as changes in motion pattern during the acquisition.

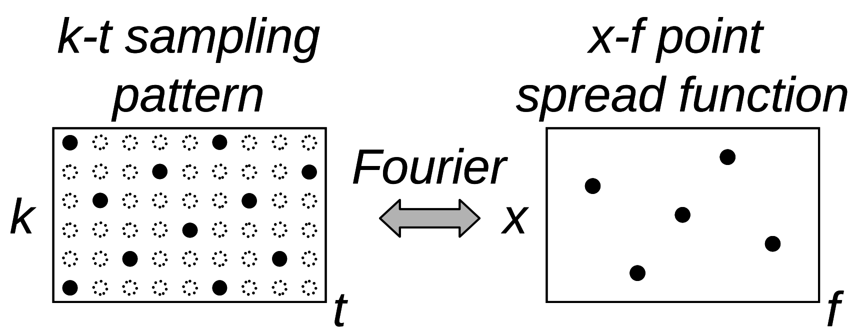

Fig.4. *k-t* sampling patterns chosen to control point spread function in *x-f* space.

Summary

Over the years, many dynamic imaging methods have been developed that take advantage of spatiotemporal correlations. By doing so, the methods are able to acquire only a fraction of the data and fill in the rest afterwards to achieve higher performance in terms of a higher frame rate, and/or shorter scan duration. In this process, image reconstruction amounts to recovering the missing information. The accuracy of the recovery is intimately linked to which data are sampled, and the *k-t* sampling pattern provides a useful conceptual tool for understanding and analyzing this aspect.

The spatiotemporal correlations of the data are used in data recovery in one of two approaches. In the more heuristic approach, nearby data are assumed to be similar, so the missing data are recovered simply with well known interpolation techniques (e.g. nearest neighbor, linear, cubic spline interpolation, etc.). For example, this approach has been used with considerable success in retrospective cardiac gating by interpolating temporally. In the second approach, one estimates the correlations directly from the data, and then applies those correlations to data recovery. This approach is more sensitive to the

accuracy of the estimation, but provides an unprecedented capability to tune specifically to the image contents.

References

1. Xiang QS, Henkelman RM. *K*-space description for MR imaging of dynamic objects. Magn Reson Med 1993;29:422-428.
2. Riederer SJ, Tasciyan T, Farzaneh F, Lee JN, Wright RC, Herfkens RJ. MR fluoroscopy: technical feasibility. Magn Reson Med 1988;8:1-15.
3. van Vaals JJ, Brummer ME, Dixon WT, Tuithof HH, Engels H, Nelson RC, Gerety BM, Chezmar JL, den Boer JA. "Keyhole" method for accelerating imaging of contrast agent uptake. J Magn Reson Imaging 1993;3:671-675.
4. Jones RA, Haraldseth O, Muller TB, Rinck PA, Oksendal AN. *K*-space substitution: a novel dynamic imaging technique. Magn Reson Med 1993;29:830-834.
5. Liang ZP, Lauterbur PC. An efficient method for dynamic magnetic resonance imaging. IEEE Trans Med Imaging 1994;13:677-686.
6. Doyle M, Walsh EG, Blackwell GG, Pohost GM. Block regional interpolation scheme for k-space (BRISK): a rapid cardiac imaging technique. Magn Reson Med 1995;33:163-170.
7. Parrish T, Hu X. Continuous update with random encoding (CURE): a new strategy for dynamic imaging. Magn Reson Med 1995;33:326-336.
8. Korosec FR, Frayne R, Grist TM, Mistretta CA. Time-resolved contrast-enhanced 3D MR angiography. Magn Reson Med 1996;36:345-351.
9. Peters DC, Korosec FR, Grist TM, Block WF, Holden JE, Vigen KK, Mistretta CA. Undersampled projection reconstruction applied to MR angiography. Magn Reson Med 2000;43:91-101.
10. Barger AV, Block WF, Toropov Y, Grist TM, Mistretta CA. Time-resolved contrast-enhanced imaging with isotropic resolution and broad coverage using an undersampled 3D projection trajectory. Magn Reson Med 2002;48:297-305.
11. Winkelmann S, Schaeffter T, Koehler T, Eggers H, Doessel O. An optimal radial profile order based on the Golden Ratio for time-resolved MRI. IEEE Trans Med Imaging 2007;26:68-76.
12. Tsao J, Behnia B, Webb AG. Unifying linear prior-information-driven methods for accelerated image acquisition. Magn Reson Med 2001;46:652-660.
13. Xiang QS, Henkelman RM. Dynamic image reconstruction: MR movies from motion ghosts. J Magn Reson Imaging 1992;2:679-685.
14. Hu X, Parrish T. Reduction of field of view for dynamic imaging. Magn Reson Med 1994;31:691-694.
15. Liang ZP, Jiang H, Hess CP, Lauterbur PC. Dynamic imaging by model estimation. Int J Imaging Syst Technol 1997;8:551-557.
16. Madore B, Glover GH, Pelc NJ. UNaliasing by Fourier-encoding the Overlaps using the temporaL Dimension (UNFOLD), applied to cardiac imaging and fMRI. Magn Reson Med 1999;42:813-828.
17. Kellman P, Epstein FH, McVeigh ER. Adaptive sensitivity encoding incorporating temporal filtering (TSENSE). Magn Reson Med 2001;45:846-852.
18. Tsao J, Boesiger P, Pruessmann KP. *k-t* BLAST and *k-t* SENSE: dynamic MRI with high frame rate exploiting spatiotemporal correlations. Magn Reson Med 2003;50:1031-1042.
19. Hansen MS, Baltes C, Tsao J, Kozerke S, Pruessmann KP, Eggers H. *k-t* BLAST reconstruction from non-Cartesian *k-t* space sampling. Magn Reson Med 2006;55:85-91.
20. Huang F, Akao J, Vijayakumar S, Duensing GR, Limkeman M. *k-t* GRAPPA: a k-space implementation for dynamic MRI with high reduction factor. Magn Reson Med 2005;54:1172-1184.
21. Malik SJ, Schmitz S, O'Regan D, Larkman DJ, Hajnal JV. *x-f* Choice: reconstruction of undersampled dynamic MRI by data-driven alias rejection applied to contrast-enhanced angiography. Magn Reson Med 2006;56:811-823.
22. Tsao J, Boesiger P, Pruessmann KP. Lattice permutation for reducing motion artifacts in radial and spiral dynamic imaging. Magn Reson Med 2006;55:116-125.