Exploiting Spatiotemporal Correlations for Dynamic Imaging

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Introduction and Purpose

For a long time the signal processing community has recognized the difference between the intrinsic content of information of a signal, and the particular representation used to describe it. The information is unique, whereas the representations are multiple. In MRI we are accustomed to use at least two representations to describe the data, image space and Fourier space, but many more surfaces all the time. Normally, the representation is chosen so that all the information is accurately portrayed. In the image compression context this is either raw format or lossless compression. In other situations, when space or bandwidth are limited, it may be convenient to use representations that store less information as long as the lost one is marginally relevant or not relevant at all. This is lossy compression.

One of the most important challenges in MRI is acquiring as much as possible information within the time frame imposed by hardware limitations and physiology processes. We want the same information acquiring less data as a way to reduce the scan time. This is particularly true for dynamic imaging where the desired frame rates impose difficult constrains for the acquisition. Fortunately, the information in dynamic images is also highly redundant (correlated). This has allowed many researchers to come up with techniques that exploit this redundancy and are able to reconstruct useful images from much less samples than one would have thought necessary.

In this lecture I will overview the meaning of information redundancy in the context of MR dynamic imaging and how it has been employed to make more efficient acquisitions.

Data Redundancy and MRI

A static image, whether from MRI or not, is easily compressed many times with any of the existing compression algorithms, JPEG for instance. That is a clear indication of the existence of redundancy, and that the information can be stored in much less space than the actual size of the image. Similarly, each time frame in a movie — or dynamic image — is also redundant. But in addition there is inter-frame correlation which adds even more redundancy and allows movie compression algorithms, MPEG for instance, achieve even greater compression rates.

In an idealized setting, one would think that it should be enough to acquire as many samples as the compressed size of the image or movie. That would be an enormous reduction in scan time, since compression rates of a hundred to one are not difficult to obtain. For this to be true one would require every measurement to be independent of any other, and that all together are enough. In other words, that we can measure all the coefficients of the basis that spans the information content, however it is defined. In general, the reconstruction becomes an inverse problem.

But the MRI acquisition happens in a setting that places very specific restrictions on the acquisition. First, the data is acquired in the Fourier domain, which in itself is not bad for the purpose of eliminating redundancy since the Fourier transform tends to produce data concentration. Secondly, hardware and physical limitations restrict the options for sampling the Fourier space, that is, only a small fraction of all k-space trajectories are feasible. Finally, Signal-to-noise ratio and desired image contrast place additional restrictions. It is also worth mentioning that in typical MRI acquisitions there is an important asymmetry between the spatial axes and the temporal axis.

In spite of the mentioned restrictions, MRI researchers have been able to device several acquisition and reconstruction techniques that exploit the data redundancy, in particular for dynamic imaging. The idea is to under-sample k-space below the Nyquist rate, and later on reduce the aliasing by exploiting spatiotemporal correlations. Some of these techniques depend on a structured under-sampling strategy, others depend on a random sampling strategy, and others are valid for both.

Statistical Sparsity

The under-sampling problem consists in finding a representation in which the data is as sparse as possible, and an acquisition technique that will allow finding those values. There are several representations which are practical for MR. Perhaps the simplest, since the data is also acquired in that domain, is to assume sparsity in k-space. Another natural representation for assuming sparsity is the image domain, which could be thought as a linear transformation of the Fourier domain. But many other representations exist, linear transformations, which could be appropriate depending on the data and application.

Fourier domain. For static images, to rely on the sparsity of the Fourier representation is difficult without compromising resolution or field of view, but for dynamic imaging, it is much more feasible. The dynamic statistical behavior of the MR signal for different location in k-space is not uniform. Some regions will stay relatively constant in time and others will change with different degrees of variation. In other words, the information content of samples in k-space is not the same. This was recognized early on, and was noted that the central part of k-space needs to be updated more frequently than the outer parts. Several techniques exploit this redundancy to increase the frame rate, such as sliding window [1], keyhole [2, 3], TRICKS [4], PROPELLER [5] and more recently VIPR [6]. Here it must be noted that differences in the information content for different parts of k-space is not only due to its different statistical properties, but also to the different psycho-visual effects they produce.

A natural extension (remember that most good ideas seem natural only after they are done!) is to treat k-space and time as a unified basis, k-t space, with its reciprocal (Fourier transformed), x-f space. It has been shown that this space is normally very sparse, with most of the energy concentrated in the hyperplane $f = 0$, and only in places where there is significant motion, there will be energy for higher values of f. Several sequences and reconstruction algorithms exploit this redundancy. UNFOLD [7] and k-t BLAST [8] recur to clever under-sampling strategies to facilitate the separation of the Nyquist aliases. It is also possible to take a more ad-hoc approach by making stronger assumptions about the expected data such as in x-f choice [9].

Image domain. Some images are already sparse in the image domain, the case of angiography for instance. This redundancy (most of the energy concentrated in only some pixels) can also be exploited, as is done by updating only a reduced field-of-view [10], or by undersampling projection reconstruction acquisitions [11].

The sparsity in image space can also be used to obtained auxiliary data, such as coil sensitivity (which are typically smooth in space and slowly variant in time) as is done in TSENSE [12] and TGRAPPA [13]. It can also be used to estimate phase to correct partial Fourier acquisitions [14, 15] or fold over suppression [16].

Other transform domains. It is not difficult to find other representations in where the information is described "more concisely." The image compression literature is full of linear and non-linear transformations; the trick for MR is to come up with a feasible reconstruction algorithm appropriate for that transformation. Perhaps one of the simplest transform is to represent the variation (either as a static Total Variation, or as a frame to frame subtraction) with respect to a reference frame [17, 18].

Some linear transforms have the property of generating sparse representation for typical images, that is the case of the discrete Fourier or Cosine transforms and of the Wavelet transform. Differently than in the previous cases, the reconstruction of this data generally requires random sampling. Compressed Sensing provides an elegant and practical framework for analyzing and reconstructing this data [19]. Interestingly, it is possible to combine the sparsity in the transformed domain with the spatiotemporal correlation in the *k-t* domain, as is done in *k-t* FOCUSS [20].

Model Based Sparsity

I will briefly mention another approach for dealing with data redundancy: model based. The idea is that there is a mathematical model of the object or objects in the image, and the reconstruction consists in finding the parameters of those models. The models could be very simple, like geometric volumes, in which case there will be only a few parameters and the data will be highly redundant, and high acceleration factors are expected. But on the other hand, simple models restrict the application because they are not able to capture complex or abnormal images which were not predicted beforehand. Nevertheless, more general application can be obtained if the model is used to estimate part of the information, such as motion [21] or temperature [22].

Models can also be very complex, in which case many parameters will be needed and therefore less sparsity is expected. One alternative is to model the signal changes in time, for example with a generalized harmonic model [23]. Models become more interesting when they do not model the time course of a voxel, but when they describe the time course of a feature (or a piece of tissue, if you will). This is the case of the "obel" technique [24].

Finally, another alternative to model is to incorporate prior knowledge into the reconstruction algorithm, see [25] for a review of several methods under a unified framework.

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