Exploring and exploiting signal correlations for reconstructing undersampled dynamic data

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Introduction The k-t SENSE (1) and recently proposed x-f choice (2) techniques can be used to reconstruct dynamic MR data undersampled in the k-t domain. The requirement for reconstruction to be accurate is redundancy in the data in the form of static or slowly changing regions, and that the aliased pixels contain fewer contributions from *dynamic* signals than can be separated with parallel imaging. This can be achieved when only a small fraction of the voxels requires high temporal bandwidth. Both methods operate in x-f space and require an estimate of the solution to discriminate aliases from signal. It is a challenge to obtain the required solution estimate and spatial and/or temporal correlations can be exploited to achieve this. Using low spatial resolution training data as with k-t SENSE translates into averaging temporal spectra over nearby spatial locations implying spatially localised temporal correlations (and requires extra data to be acquired). The properties of x-f space suggest that knowledge of the precise location of different types of temporal information would be better; we will analyse how to obtain this information directly from aliased data in the presence of often low SNR.

Method Starting with a fully sampled x-f space, we define 'temporal correlation' to describe voxels with similar magnitude spectra at non zero frequencies. DC is always excluded since variation solely due to static features is irrelevant. We can define a space P such that the magnitude *f*-spectrum (excluding DC) of a given voxel gives its position vector in P. Closeness in this space therefore implies temporal correlation. Local averaging in P can be used to combine temporally correlated signals from any part of the image, allowing us to produce a high SNR 'model' of the true data. A useful property of x-f data is that in general, frequency spectra are strongly peaked at low |*f*|. As a result we can look for temporal correlations by comparing only low frequencies over some range Δf (marked on fig 1a) – call this space P'. The signal profiles generally assume certain shapes and hence in P' the distribution of voxels is highly correlated. It is possible to identify these correlations with PCA and then further reduce the basis to say two dimensions – a helpful tool for visualisation but also for computational efficiency - call this space F (fig 1b). Since *f*-spectra are highly peaked, we may form space F from aliased data. In this case some voxels may be displaced in F due to aliasing; however multiple coil information can be used to remove such errors.

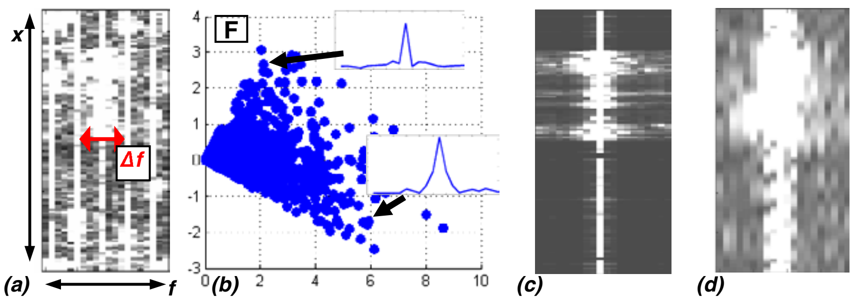

Fig 1 **a)** Five fold undersampled x-f space (cardiac data) **b)** F space: each spot marks one voxel (only a random subset plotted). Inset spectra show spectral shapes of voxels in indicated region. **c)** x-f space model generated by current method **d)** equivalent low resolution training data acquired with standard k-t SENSE protocol.

Space F provides a way of constructing a signal distribution model directly from aliased data. Absolute values in F provide information on "how dynamic" a voxel is: information which can be used to decide which voxels alias only with static ones and therefore contain correct information over the full *f*-FOV, and which contain information damaged by aliasing. It is possible to then locally average full bandwidth spectra depending on the voxels' locations in F, over only voxels deemed to not contain aliasing artefacts. This generates, for each local neighbourhood in F, an estimate of the full bandwidth temporal frequency spectrum. These averaged spectra can be associated with voxels local in F that were damaged by aliasing: in this way we can generate an estimate of the signal distribution in un-aliased x-f space (fig 1c) directly from regularly undersampled data. In reality since complex spectra are averaged, the phase needs to be taken into account to avoid signal loss - this information is missing from F. For each space mentioned previously we can add linear phase variation across the spectrum as an extra dimension. Taking account of phase allows strong noise suppression with limited signal cancellation. The method has been used to provide models for reconstruction of data from both CE angiography (3 datasets) and cardiac imaging (3 datasets) with both x-f choice and k-t SENSE. The model has favourable properties for both of these techniques; it has the same resolution as the data and importantly has a high relative SNR, greatly boosted by strong suppression of noise in static voxels.

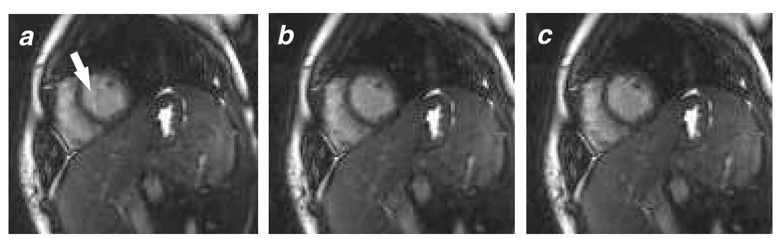

Fig 2 Same slice and phase from **a)** k-t SENSE reconstruction with low resolution training data, **b)** k-t SENSE using model **c)** x-f choice using model. Arrow on **a** marks position of alias artefact

Results Results from angiography were similar to those previously published (2). Undersampled volumetric cardiac data were obtained using a Philips 1.5T scanner with a commercial implementation of k-t SENSE and a 5-channel receiver. A 20 phase, 15 slice data set was acquired in a single breath hold (healthy volunteer, 30 sec) using 5 fold undersampling and interleaved training data. When reconstructed with k-t SENSE using low resolution training data (fig 2a) a prominent residual flickering alias artefact of the edge of the heart (arrow, fig 2a) was present in both our implementation and that of the scanner. This artefact is not apparent in k-t SENSE reconstruction using the x-f model as training data (fig 2b), we suppose because edge information not present in the low resolution training data is present in the model. The x-f choice reconstruction (fig 2c) contains noticeably crisper edges at the myocardium-blood pool boundary during periods of rapid motion; however has a lower SNR in these regions. This is to be expected because the latter method allocates the necessary temporal bandwidth in these regions without trading it for noise suppression.

Conclusions Presented is a general method for identifying and exploiting temporal correlations between spatially independent voxels in order to create a model of the x-f signal distribution from regularly undersampled dynamic data, primarily for use in reconstruction of such data. Low resolution training data is a pragmatic solution that assumes spatial correlation - i.e. adjacent voxels behave similarly - leading to loss of information about rapidly changing small features. In general, correlations are exploited to obtain the reference data but are not directly involved in the final reconstruction. We have shown that it is possible to construct a model without use of extra data and that as well as being well suited for x-f choice, k-t SENSE reconstruction quality can improved with this technique.

References **1**. Tsao J et al., MRM. 2003 Nov;50(5):1031-42. **2**. Malik SJ et al., MRM. 2006 Oct;56(4):811-23

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