Dynamic Images Reconstruction using *kt*-BLAST without Training Data

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INTRODUCTION: Acquiring a series of images with high spatial and temporal resolution simultaneously is very desirable in dynamic cardiac imaging. The *kt*-BLAST technique [1] [2] (*k*: *k*-space domain, *t*: time domain) has recently been proposed to speed up these acquisitions. It is based on undersampling the *k*-space in the phase encoding direction and time, and exploits the redundancy in the images to learn the spatiotemporal correlations of the imaged objects. This learning step is done by acquiring additional low-resolution, fully sampled data (called training data) interleaved with the actual *kt* scan in order to resolve the introduced aliasing. In this work, we show on a simulated *kt* acquisition that the information contained in the undersampled acquired data can be used to reconstruct the images without having to acquire a training data set and so save the additional time used in acquiring the training data for either having a higher temporal resolution or reducing the breath-hold duration.

METHOD: The *kt*-BLAST acquisition consists in: 1) acquiring an undersampled data set as proposed in [1] and, 2) acquiring the training data, consisting the central lines (from 3 to 11 profiles) of the *k*-space at the same frame rate as the *kt* data. This additional scan when done separately, takes 5 to 10 sec and the corresponding images have a very low resolution. The *kt* reconstruction is performed in the *y-f* space (*y*: spatial position, *f*: temporal frequency) by optimising a function composed of a data consistency term and a prior term. This latter term is constructed from the low-resolution training scan. We propose replacing the training data by a sliding window reconstruction of the undersampled acquisition which can be used to interpolate the missing data along the time direction. We refer to this method as *self-training*.

The sliding window interpolation was done by convolving the data with a triangular kernel along time. This is equivalent to multiplying the *y-f* space by a squared sinc function:

$$\mathrm{FT}\{s_W(ky,t)\} = \mathrm{FT}\{s(ky,t) \otimes h(ky,t)\} = S(y,f)\ .\ H(y,f),$$

where FT is the Fourier transform operator, $s\,(ky,t)$ is the undersampled data in *k-t* space and *h* is the convolution kernel. We can see on Fig. 1 that, on the left, the sliding window interpolation attenuates the aliases, without separating them, in the higher temporal frequencies (*f* direction) and introduces periodic zeros in the *y-f* space. Applying the kt reconstruction and combining it with the sliding window as prior, we see that the method has performed an interpolation along *f*, which recovers some of the missing information and thus reduces the aliasing.

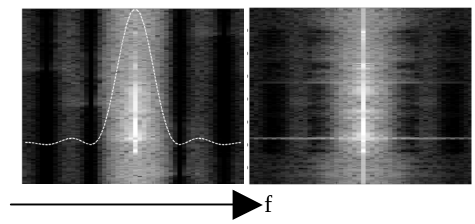
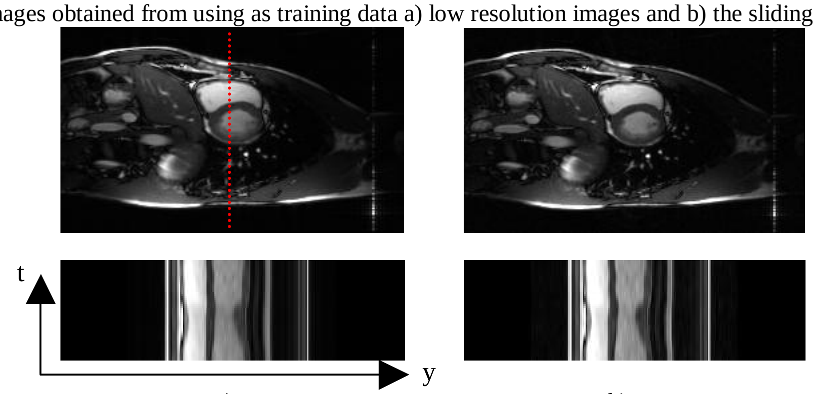


Fig. 1: *y-f* space a) Sliding Window, b) KT reconstruction

RESULTS: This method was applied to simulated *kt* images and compared to a standard *kt* reconstruction. A fully sampled retrospectively gated 2D short axis cine was acquired from a volunteer in a Philips Intera 1.5T scanner using a SSFP sequence (50 phases, 160×256 acquisition matrix, 8 mm slice thickness). This data was undersampled by a factor of 5 using Matlab (Mathworks) with a skewed *kt* pattern as proposed in [1]. Fig. 2 shows near end-systole short-axis images obtained from using as training data a) low resolution images and b) the sliding window approach.



a) b)

Fig. 2: a) *kt* with low-resolution Training Data. Top: modulus image, bottom: profile across time.
b) *kt* with sliding window Training Data. Top: modulus image, bottom: profile across time.

DISCUSSION & CONCLUSION: Using the sliding window as an estimate of the spatiotemporal correlations for the *kt* reconstruction allows this to be done without having to acquire an additional training data set. Visual comparison of the images indicates that the spatial and temporal resolution with the self-training approach is as good as standard *kt* reconstruction using acquired training data (see *y-t* images in Fig. 2). Even though the sliding window derived training data was not free of aliasing artefacts, the aliasing has been reduced and is not noticeable in the images (Fig. 1.b). This shows that the *kt* reconstruction is robust and that as long as we use training data which is close enough to the real dynamic changes in the cine images such as a sliding window reconstruction of the sparse data, we are able to obtain an acceptable solution to the *kt* reconstruction problem and remove most of the aliasing. Further research is needed to quantify any loss of information resulting from the omission of the training data. Self-training opens the way to applying *kt* to cardiac images without the need for training data acquisition and so reducing the scan time, and making it applicable to situations where motion is not reproducible.

REFERENCES [1] J. Tsao et *al.* MRM 50,5 2003**,** [2] J. Tsao et al. ISMRM 2003 ; 209