k-t denoising – exploiting spatiotemporal correlations for signal-to-noise improvement in dynamic imaging

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Introduction The signal-to-noise ratio (SNR) of MRI is often at a premium, particularly for small-animal imaging. In many cases, signal averaging provides a necessary, but time-consuming, means of gaining sufficient SNR for proper post-processing, such as segmentation. The present work proposes a new method for improving SNR in dynamic imaging, by exploiting the spatiotemporal correlations within time-resolved images, such as cine images of the heart. The proposed approach is called *k-t* denoising. It can be considered a limiting case of the recently proposed *k-t* BLAST and *k-t* SENSE methods [1] without acceleration. In this case, *k-t* space is fully sampled (*k* = spatial frequency, *t* = time), which opens up additional opportunities, such as the use of alternative and more effective transforms.

Theory The *k-t* reconstruction formula is as follows [1]:

$$\rho = \Theta E^H (E\Theta E^H + \Psi)^+ d \qquad [1]$$

where ρ is the reconstructed voxel in *x-f* space, with *x* and *f* denoting spatial position and temporal frequency, respectively. Θ is the signal covariance matrix, E is the encoding matrix, Ψ is the noise covariance matrix, d is the data vector in *x-f* space. When there is no acceleration, Eq. [1] adopts the form of a Wiener filter in *x-f* space (Fig. 1). The data are split into two paths. The first undergoes spatial filtering to yield the equivalent of the training data in *k-t* BLAST and *k-t* SENSE. The second is then combined with the training data in *x-f* space according to Eq. [1] for denoising. Since the data are fully sampled, this opens up the possibility of choosing alternative transforms other than the Fourier transform, without losing computational efficiency. In that case, "*f*" no longer corresponds to temporal frequency, but simply a conjugate axis of time. In the present work, we applied either the Fourier transform or a singular value decomposition (SVD) [2] for comparison. The latter is chosen, since it is automatically adaptive to the data.

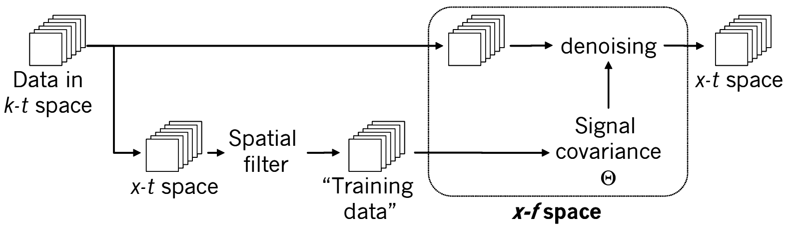

Fig. 1 Overall scheme of *k-t* denoising. The data are split into two paths. One of the path (bottom) undergoes spatial filtering to provide information for estimating the signal covariance, which is used in the denoising step. The other path (top) undergoes transformation to *x-f* space, where denoising takes place. The denoised data are converted back to the *x-t* space as the final output.

Methods To evaluate the method, *in vivo* cardiac images were acquired from healthy but genetically obese ob/ob mice. Images were acquired with EKG triggering on a Bruker 4.7T PharmaScan MRI (Bruker BioSpin, Ettlingen, Germany) using a gradient-echo sequence (TE/TR/flip = 1.34ms/10ms/30deg). Due to body size, the images with the ob/ob mice were acquired with a rat volume coil. All experiments were conducted in accordance to institutionally approved protocols.

Results Fig. 2 shows cardiac images in an end-diastololic 4-chamber view. For the training images, it can be seen that low-pass filtering in Fourier domain led to significant blurring as expected (2nd from left), whereas blurring was reduced in the SVD domain (4th from left). In turn, this translated to slightly improved noise removal with the SVD domain (5th from left). Fig. 3a shows cine short-axis cardiac images from an ob/ob mouse. The difference before and after denoising was amplified 5 times to depict details. The difference image shows that the removed component was noiselike, so the filtering did not result in any discernable loss of image details. The extent of noise removal was adaptive and spatially varying, as expected from the *k-t* theory. Spatiotemporal (*x-t*) plots are shown in Fig. 3b, corresponding to the dotted white profile in Fig. 3a. These *x-t* plots indicate that the denoising was able to preserve the overall temporal fidelity of the dynamic series.

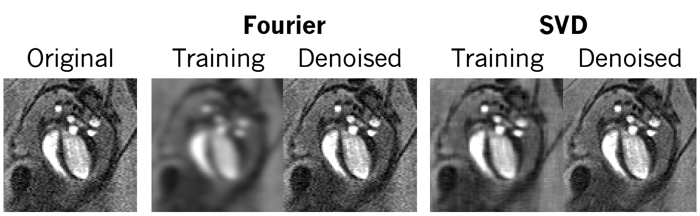

Fig. 2 Comparison of Fourier and SVD transforms in *k-t* denoising of cine cardiac images of an asymptomatic FVB mouse. From left to right: original image in diastole, corresponding training image by low-pass filtering in Fourier domain, Fourier-denoised image, training image by low-pass filtering in SVD domain, SVD-denoised image.

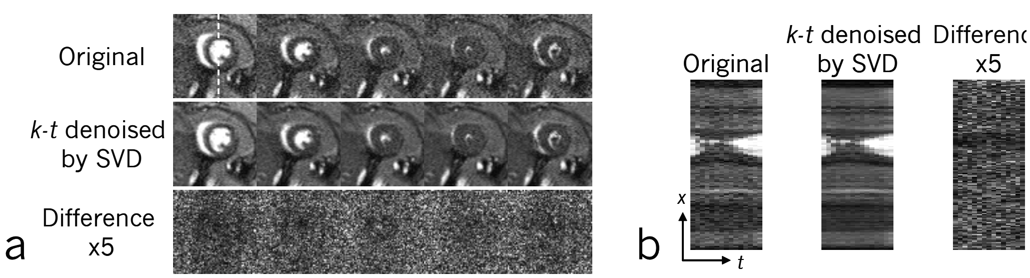

Fig. 3a. Cine cardiac images of an ob/ob mouse before (top) and after (middle) denoising, and the difference amplified 5x (right). b. The corresponding spatiotemporal (*x-t*) plots along the profile indicated by white dotted line in 3a.

Discussion *k-t* denoising is a post-processing method that significantly reduces noise by exploiting spatiotemporal correlations within an image series. It shares some similarities with wavelet denoising [2-3]. In fact, the generation of the training data is equivalent to wavelet denoising, with the wavelet transform being replaced by a different transform. The novelty of the present work is to utilize this as an initial estimate, and then apply a second denoising step in the *x-f* domain. Therefore, the correlations along both space and time are fully taken into account. In this work, we have shown that SVD provided improved data compression compared to the Fourier transform, which led to improved noise reduction, while retaining high fidelity of the images. In practice, this translates to the need for fewer signal averages and thus reduced scan duration.

References [1] Tsao J, et al. Magn Reson Med, 50, 1031-42. 2003. [2] Zientara GP, et al. Magn Reson Med, 32, 268-74. 1994. [3] Weaver JB, et al. Magn Reson Med, 21, 288-95. 1991. [4] Donoho DL. IEEE Transactions on Information Theory, 41, 613–627. 1995.