### Highly accelerated cine phase-contrast flow measurements using k-t PCA with spatial compartments

#### D. Giese<sup>1,2</sup>, V. Knobloch<sup>1</sup>, H. Pedersen<sup>3</sup>, T. Schaeffter<sup>2</sup>, and S. Kozerke<sup>1,2</sup>

<sup>1</sup>Institute for Biomedical Engineering, University and ETH Zurich, Zurich, Switzerland, <sup>2</sup>Division of Imaging Sciences, King's College London, London, United Kingdom, <sup>3</sup>Functional Imaging Unit, Glostrup Hospital, Glostrup, Denmark

Introduction: Scan acceleration of phase-contrast MRI by parallel imaging [1,2] and spatio-temporal acceleration techniques [3,4] has been demonstrated with net reduction factors of 2-5 achievable in practical situations. This has permitted single directional flow quantification with clinically valuable spatiotemporal resolution in a single breathhold. Temporally constrained reconstruction techniques have recently been proposed to achieve reduction factors beyond previous limits [5,6]. In this work, k-t PCA [6] is extended by defining spatially specific temporal constraints. The method which is referred to as k-t PCA+ is demonstrated to enable accurate flow quantification up to 20-fold nominal undersampling corresponding to 10-fold net scan time reduction when the acquisition of training profiles is taken into account.

Methods: In k-t PCA, the signal  $\rho(x, f)$  in the spatio-temporal frequency domain is decomposed, by a principle component analysis (PCA), into temporal basis functions B(f) corresponding to the principle components PC in the temporal frequency domain and spatially dependent weighting coefficients w(x):

### $\rho(\mathbf{x}, \mathbf{f}) = \mathbf{w}(\mathbf{x})\mathbf{B}(\mathbf{f}).$

The weighting coefficients are reconstructed in a regularized least-square sense [7] as follows:

# $w_x = M_w^2 E_w^H (E_w M_w^2 E_w^H + \sigma I)^+ w_{alias.x}$

The vector  $w_x$  correspond to the unfolded spatial weighting,  $w_{alias,x}$  to the aliased signal weightings,  $M_w^2$  to the diagonal elements of the weighting covariance matrix derived from lowresolution training data,  $E_w$  to the encoding matrix and  $\sigma$  to the noise variance in PC space. Since signal energy of typical dynamic objects is concentrated in the first few principle components of the temporal frequency domain, the sparse representation of the signal in PC space greatly reduces the number of unknowns to solve for [6]. Furthermore, the method constrains the reconstructed image to follow the temporal behavior described by the temporal basis functions B(f) assuming that the temporal basis derived from low-resolution training data reflects the temporal behavior in the undersampled data.

To enhance the k-t PCA method, n spatially specific basis functions sets  $B_n(f)$  of n spatial compartments with similar temporal behaviors are defined. Thereby the total number of significant basis functions is further reduced. Definition of compartments is based on correlations of temporal variance in the image phase of cine phase-contrast data. The number of compartments depends on the number of vessels or groups of vessels present in the image slice. In the present work a total of three independent spatial compartments was defined corresponding to the

ascending aorta, the descending aorta and all remaining tissue (Figure 1). Cine phase-contrast velocity data were obtained in transverse orientation at the level of the pulmonary artery in healthy subjects on a 1.5T Philips Achieva system (Philips Healthcare, Best, The (field-of-view:320x260mm<sup>2</sup>, Netherlands) matrix:128x104. temporal resolution: 20 ms, venc:1.2 m/s). Nominal undersampling factors of R=2 to R=20 were simulated for different numbers of training profiles (#TP=3 to 21). Images were reconstructed by incorporating all five elements of the receive coil array in the encoding matrix and, additionally, by using only the coil element nearest to the vessel in order to demonstrate the capability of the method to perform well with as few as a single coil element. Volume flow was calculated for the ascending and descending aorta for different nominal reduction factors and training data profiles and compared to values derived from fully sampled data.

Results: Figure 2 shows flow profiles of the ascending and descending aorta for R=16 and 7 training profiles (net acceleration of 8) reconstructed with k-t SENSE, k-t PCA and k-t PCA+ along with the result from fully sampled data. Whereas k-t SENSE shows significant smoothing of the curve, k-t PCA+ achieves excellent reconstruction fidelity. In contrast to k-t PCA and k-t SENSE, k-t PCA+ does not suffer from temporal filtering effects. Forward and retrograde flows are accurately reconstructed. The root-meansquare error (RMSE) as a function of acceleration factor and as a factor of the number of training profiles used is shown in Figure 3. The RMSE of flow values derived from k-t PCA+ stays in the order of 5-10% for all acceleration factors given a minimum number of 7 training profiles.

Discussion: It has been shown that spatial compartments can be incorporated into the k-t PCA framework improving data fidelity at very high acceleration factors. The method proved very robust even when only a single coil element was used rendering it suitable on all systems regardless of the available number of receiver channels. Velocity mapping in the ascending and descending aorta with 10fold net undersampling demonstrates the potential of the method for highly accelerated flow measurements.



Figure 1: Based on the temporal behavior of the low resolution training data (top), a variance map followed by thresholding defines two compartments. Accordingly, separate basis functions for the ascending (yellow), descending (blue) aorta and the remaining tissue (green) are calculated.

w(x)B(f



Figure 2: Flow profiles of the ascending (left) and descending (right) aorta, calculated from 8fold net undersampled images and reconstructed using k-t SENSE, k-t PCA, k-t PCA+ as well as using a single coil only in *k*-*t* PCA+ (*SC k*-*t* PCA+)



Figure 3: Flow profile RMSE for ascending and descending aorta as a function of acceleration factors (left) and number of training profiles (TP) (right). The net acceleration factor (R<sub>net</sub>) is displayed for each acquisition.

[1]Thunberg P et al. Magn.Reson.Med. 2003;50:1061–1068 [2]Beerbaum P et al Circulation 2003;108:1355–1361 [3]Baltes C.et.al.Magn.Reson.Med.2005;54:1430-8 [4]Jung.B.et.al.Magn.Reson.Med.2008;60:1169-1177 [5]Liang ZP.et.al.ISBI.2007:988-991 [6]Pedersen H.et.al.Magn.Reson.Med.2009;62:706-716 [7]Tsao.J,et.al.Magn.Reson.Med. 2003;50:1031-1042

## **References:**