Optimized *model-based* undersampling and reconstruction for dynamic MRI based on *support splitting*.

Application to phase contrast MRI carotid blood flow imaging.

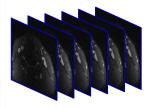
Gabriel Rilling¹, Mike Davies¹, Yuehui Tao² and Ian Marshall²

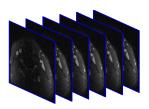
 ¹Institute for Digital COMmunications (IDCOM), University of Edinburgh
 ²Medical Physics, University of Edinburgh



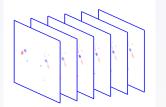
Phase contrast carotid blood velocity imaging

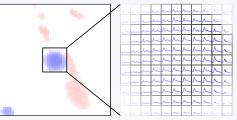
Two sets of images:





Reference frames Velocity encoded frames Velocity information: phase difference



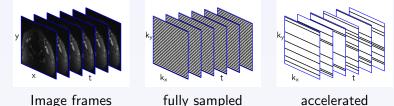


Phase difference frames

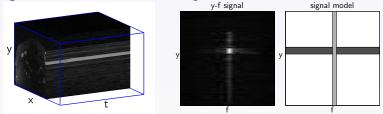
Right carotid artery blood velocity

Phase contrast carotid blood velocity imaging

Signal acquisition: lines in the Fourier domain (*k*-space)

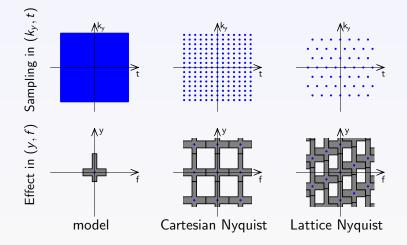


Signal model for one line through the carotid



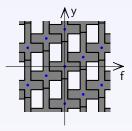
Traditional accelerated dyn-MRI (UNFOLD, PARADIGM)

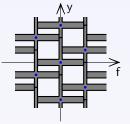
Lattice sampling 2D version of classical sampling theory



Traditional accelerated dyn-MRI (UNFOLD, PARADIGM)

The performance of lattice sampling depends on packability

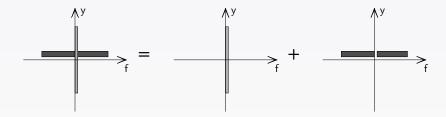




decent acceleration

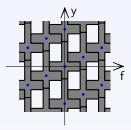
poorer acceleration

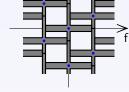
Possible improvement: split the support for improved packability



Traditional accelerated dyn-MRI (UNFOLD, PARADIGM)

The performance of lattice sampling depends on packability

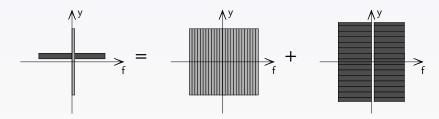


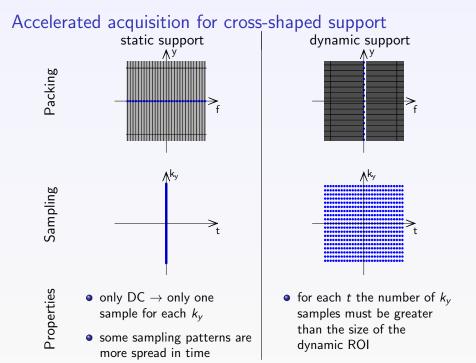


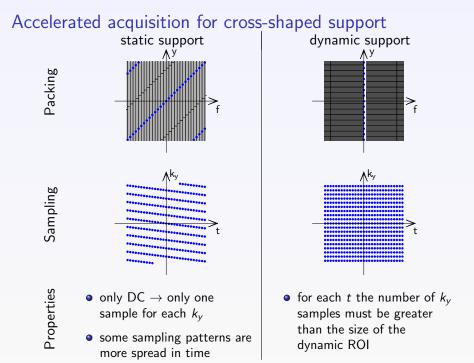
decent acceleration

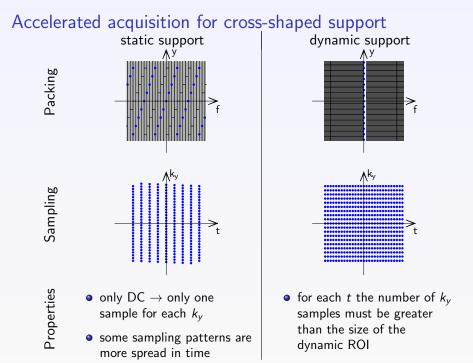
poorer acceleration

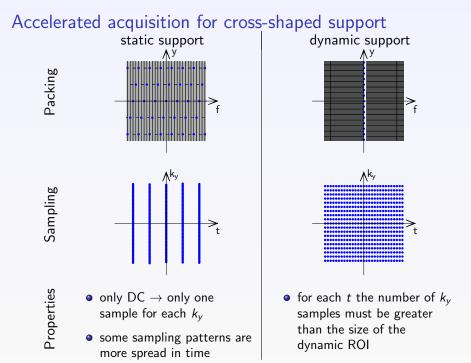
Possible improvement: split the support for improved packability

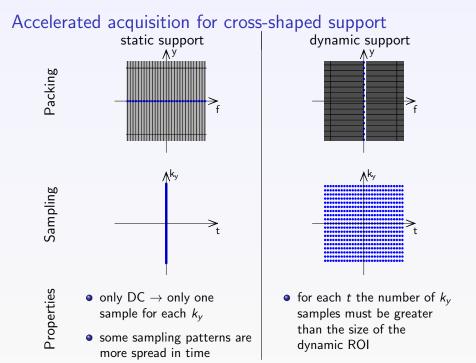


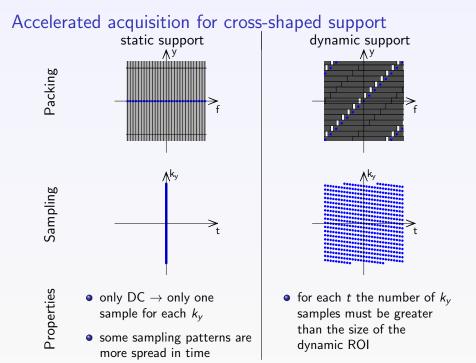


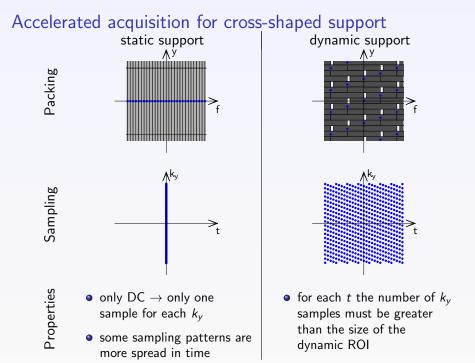


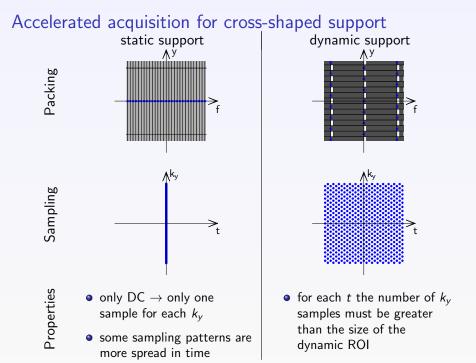










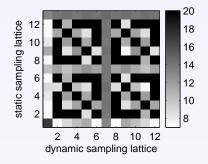


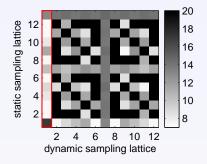
Accelerated acquisition for cross-shaped support

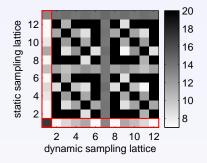
Properties of the support splitting approach

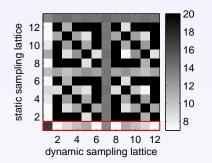
- Allows much higher acceleration factors
 up to minimum sampling rate for a cross-shaped support
- Penalty in terms of conditioning for the reconstruction
 - single lattice sampling: condition number = 1
 - ${\, \bullet \,}$ two lattices sampling: condition number > 1
- $\bullet\,$ Different combinations of two lattices \rightarrow different conditioning

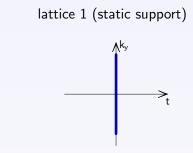
- *Finite number of lattices* given a support shape and image/time resolution
- conditioning can be optimized via exhaustive search





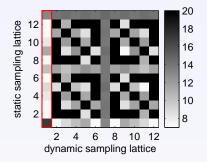






Properties

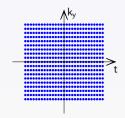
- All samples at the same time location in the cycle
- ⇒ Not applicable for acceleration!

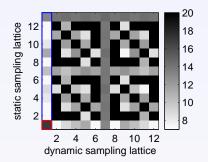


Properties

- Samples aligned along lines of constant k_v locations
- Can be achieved with retrospective gating

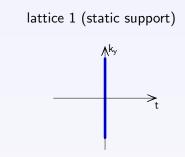
lattice 2 (dynamic support)

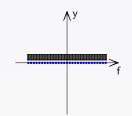


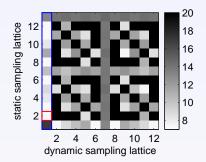


Properties

- Condition number: pprox 17
- No spread over time
- No spread of the dyn. support



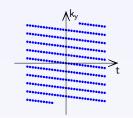


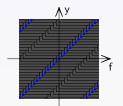


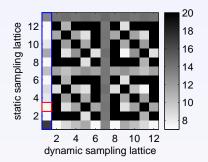
Properties

- Condition number: pprox 7.4
- Maximum spread over time
- Maximum spread of the dyn. support

lattice 1 (static support)

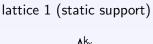


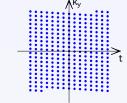


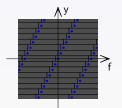


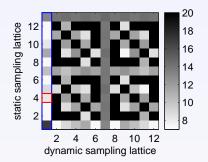
Properties

- Condition number: pprox 7.4
- Good spread over time
- Maximum spread of the dyn. support



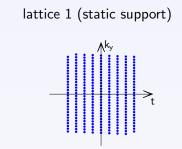


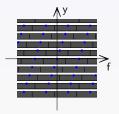


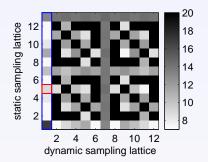


Properties

- Condition number: pprox 8.2
- Poor spread over time
- Poor spread of the dyn. support

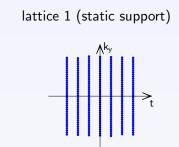


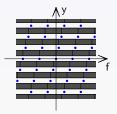


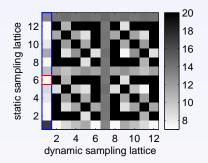


Properties

- Condition number: ≈ 9
- Poor spread over time
- Poor spread of the dyn. support



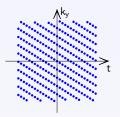


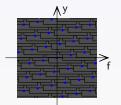


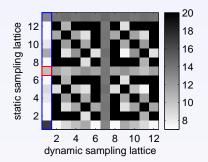
Properties

- Condition number: pprox 7.4
- Maximum spread over time
- Maximum spread of the dyn. support

lattice 1 (static support)



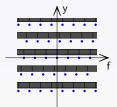


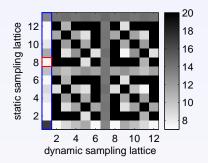


Properties

- Condition number: pprox 10.3
- Poorer spread over time
- Poorer spread of the dyn. support

lattice 1 (static support) $\xrightarrow{\Lambda^{k_y}}_{t}$

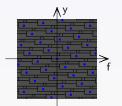


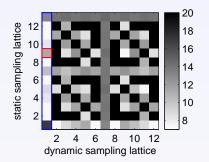


Properties

- Condition number: pprox 7.4
- Maximum spread over time
- Maximum spread of the dyn. support

lattice 1 (static support)

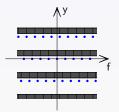


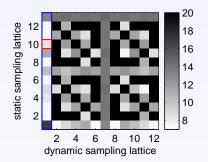


Properties

- Condition number: pprox 11.4
- Poorer spread over time
- Poorer spread of the dyn. support

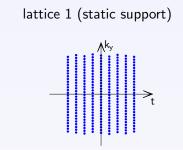
lattice 1 (static support) $\xrightarrow{\Lambda^{k_y}}_{t}$

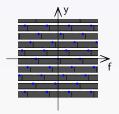


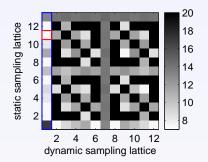


Properties

- Condition number: pprox 8.2
- Poor spread over time
- Poor spread of the dyn. support

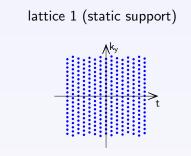


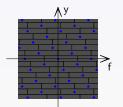


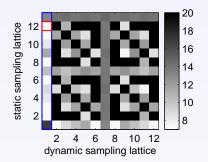


Properties

- Condition number: pprox 7.4
- Good spread over time
- Maximum spread of the dyn. support

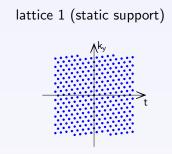


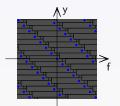


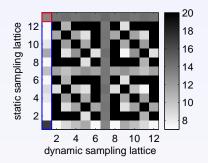


Properties

- Condition number: pprox 7.4
- Maximum spread over time
- Maximum spread of the dyn. support



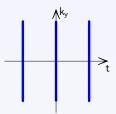


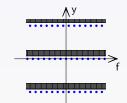


Properties

- Condition number: pprox 13.2
- Very poor spread over time
- Very poor spread of the dyn. support

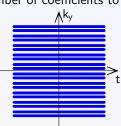
lattice 1 (static support)





Application to carotid blood flow imaging Detection of the dynamic support

- Block support: typically one block in y (or a very small number)
- The correct support should provide the best fit to the measurements in the least-squares sense
- The previous sampling pattern alone is insufficient because the number of measurements is equal to the number of coefficients to estimate Λ^{k_y}
- Multi-coset sampling may be used to detect one (or several) blocks



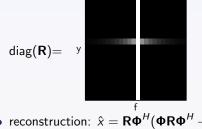
Reconstruction algorithm

- Exhaustive search of the block-sparse dynamic support minimising the residual $(O(N^{N_b})$ possibilities for N_b blocks)
- Global reconstruction using pseudoinverse (actually obtained in the previous step)

Application to carotid blood flow imaging -2

Possible improvements

- 2D search for the dynamic support assuming a circular shape in the image
- use Wiener estimation: minimize $\mathbb{E} \|\hat{x} x\|_2$ assuming
 - observation model $y = \mathbf{\Phi} x + n$ with $n \sim \mathcal{N}(0, \sigma^2 \mathbf{I})$
 - signal model: $x \sim \mathcal{N}(0, \mathbf{R})$ with diagonal **R**:



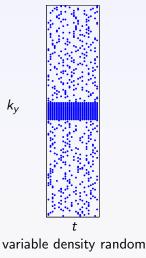
- constant static support
- exponential decay in frequency
- can be calibrated using standard pseudoinverse reconstruction

• reconstruction:
$$\hat{x} = \mathbf{R} \mathbf{\Phi}^{H} (\mathbf{\Phi} \mathbf{R} \mathbf{\Phi}^{H} + \sigma^{2} \mathbf{I})^{-1} y$$

• use information from multiple coils (receivers)

Examples of sampling patterns (5X acceleration) support splitting

compressed sensing



cond. ≥ 200

 k_v

multi-coset dynamic + well-spread static cond. ≈ 6.2

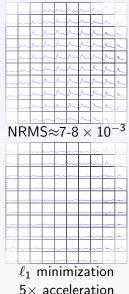
Examples of reconstructions (simulations)

support splitting NRMS= 9×10^{-3} $NRMS = 8.1 \times 10^{-3}$

Wiener estimation

 $5 \times$ acceleration

compressed sensing



error

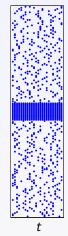
Pseudoinverse

 $5 \times$ acceleration

reconstruction

Improving the sampling pattern support splitting

compressed sensing



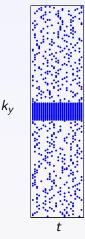
 k_v

1

 k_v

Improving the sampling pattern support splitting

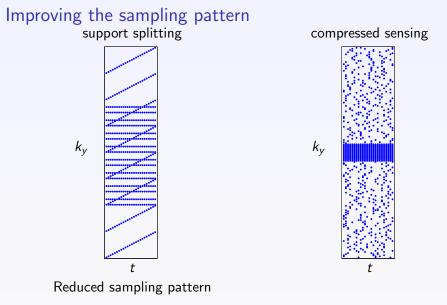
compressed sensing



 k_v

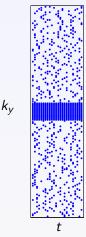
t

High spatial frequencies can be assumed constant



Improving the sampling pattern support splitting

compressed sensing



 k_v

†

Reduced sampling pattern with simulated high spatial frequencies

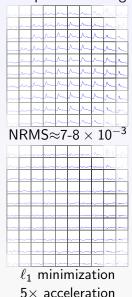
Examples of reconstructions (simulations)

support splitting reconstruction $NRMS = 8.1 \times 10^{-3}$ NRMS= 7×10^{-3} error Wiener estimation "low-pass" Wiener

 $5\times$ acceleration

8.2× acceleration

compressed sensing



Conclusions

Deterministic approach based on

- support splitting
- multi lattice sampling

Properties

- Allows high acceleration factors
- Competitive with state of the art compressed sensing methods (k-t SPARSE, k-t FOCUSS,...)
- Controlled condition number

⇒ guarantees on the reconstruction quality

Applications

- Phase contrast carotid blood flow imaging
- functional MRI

• . . .

Thank you for your attention