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# N/eu/ro/Sp/j/n

PARIETAL

SFB workshop, Graz, Austria Imaging with Modulated/ Incomplete Data 2016



### **Compressed Sensing in MRI:**

How the maximum undersampling factor depends on the image size and the SNR?

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#### INTRODUCTION HIGH RESOLUTION



2D T2\*w axial, 7T scanner 120 x 120 x 600 µm<sup>3</sup> Matrix size: 1690 x 1744 21 slices, 2 averages 32-channel receiver coil, Motion correction

Acquisition Time of 50 minutes! *How can we* 

accelerate this?



#### **One solution to reduce the acquisition time**:

Undersample the Fourier data using Compressed Sensing theory.

- Is there a practical user guide to select the appropriate undersampling factor in the particular case of CS-MRI?
- How do we define « appropriate » ?
- What are the factors influencing this choice?



- From the traditionnal CS theory...
  - ➤ To faithfully recover a signal with s on-zero entries: number of required measurements: m = O(s·log(n)) where n=#pixels
  - ➔ Noisy case: still holds but a larger error





#### INTRODUCTION BACKGROUND

- From the traditionnal CS theory...
  - → To faithfully recover a signal with s on-zero entries: number of required measurements:  $m = O(s) \log(n)$  where n=#pixels
  - ➔ Noisy case: still holds but a larger error

- ... to a CS adapted to MRI
  - CSMRI [Lustig et al. 2008]
  - Variable Density Sampling

[Puy et al. 2011]



• Breaking the coherence barrier: A new theory for Compressed Sensing [Adcock et al. 2013]

« The success of compressed sensing is resolution dependent »



# What is the maximum degree of acceleration that can be applied in a given situation?

- 1. The larger the image size, the more you can undersample.
- 2. The larger the input SNR, the more you can undersample.

#### **Our objectives:**

- We want to verify these intuitions with simulations and experiments.
- We want to offer quantitative guidance to choose a proper undersampling factor as a function of image size and SNR and desired image quality.



- I. Materials and methods
  - Simulations
  - Experiments
- II. Results
  - Resolution dependence
  - SNR dependence
  - $R_{max}(\varepsilon, N, SNR)$
  - MR feasible sampling schemes
- III. Discussion and conclusion



II. MATERIALS AND METHODS A. SIMULATIONS

## **MATERIALS and METHODS**

## Simulations



#### II. MATERIALS AND METHODS A. SIMULATIONS - IMAGES

• Analytical phantom of T2-like brain image (infinite SNR) [Guerquin-Kern et al. (2012)]

Matrix sizes: N = 128, 256, 512, 1024 or 2048

Number of pixels: *n*=*N*<sup>2</sup>

- Addition of complex-valued Gaussian noise, with growing standard deviation, to the Fourier data
- Calculation of the input SNR on magnitude image:

SNR = S /  $\sigma$ 

- S = mean signal in a ROI in white matter
- $\sigma$  = standard deviation in the background
- ➔ SNR ranges from 6 to 110







#### II. MATERIALS AND METHODS SIMULATIONS - UNDERSAMPLING

- Retrospective undersampling factors  $R=N^2/m$  ranging from 2 to 30
- Variable Density Sampling with a polynomial decay of 1/|k|<sup>2</sup>



Radial view of density



2D view of density



Not MR feasible but provides near upper bounds to sampling performances



Samples in k-space N=512 and R=5

- Example of **MR feasible sampling schemes** 
  - Radial golden angle [Winkelmann et al. (2007)]





• L2-L1 penalized CS problem:



- NFFT [Keiner, Kunis and Potts, TU Chemnitz]
- Redundant wavelets from RICE university toolbox
- Constant regularization parameter  $\lambda$ =10<sup>-4</sup>
- FISTA algorithm [Beck & Teboulle (2009)]



#### II. MATERIALS AND METHODS SIMULATIONS – IMAGE QUALITY METRIC

- SSIM: The Structural SIMilarity (SSIM) index [Wang et al. (2004)]
  - Measures the similarity between 2 images.
  - *SSIM(I, Iref)* = 0 : null correspondence.
  - SSIM(I, Iref) = 1 : perfect match.
  - A measure closer to the human perception of error in an image than traditional error metrics such as MSE or pSNR.
  - MR main customer: physicians and radiologist.
- Our choice of reference:

The corresponding full Cartesian image with a high input SNR of 110.

• What SSIM threshold?

Cea

#### II. MATERIALS AND METHODS SIMULATIONS – IMAGE QUALITY THRESHOLD

#### Reference



We choose an image quality threshold of:

SSIM ≥ 0.9





II. MATERIALS AND METHODS EXPERIMENTS

## **MATERIALS and METHODS**

**Experiments** 



#### II. MATERIALS AND METHODS B. EXPERIMENTS

• Ex-vivo brain baboon in fluorinert solution

#### Sequence parameters

- 7T Siemens healthineers scanner
- In vivo Corp Birdcage 1Tx/1Rx coil
- T2\* weigthing
- Slice thickness: 5 mm
- TR = 60 ms
- TE = 30 ms
- $\alpha = 10^{\circ}$
- Axial slice
- Signal averaging to increase input SNR





Full Cartesian acquisition N=512 of SNR = 110



#### I. Materials and methods

- Simulations
- Experiments

#### II. Results

- Resolution dependence
- SNR dependence
- $R_{max}(N, SNR)$
- MR feasible sampling schemes

III. Discussion and conclusion

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#### II. RESULTS

## **Resolution dependence**

How should the acceleration factor be chosen as a function of image size ?

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#### **RESOLUTION DEPENDENCE**



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#### **RESOLUTION DEPENDENCE**



- There is a restricted number of authorized combinations:
  - R=5 works for N≥256
  - R=10 works for N≥512
  - R=20 works for N≥2048
  - ...
- Do these figures make sense on experimental data?

## 

#### **RESOLUTION DEPENDENCE EXPERIMENTS - VISUALIZATION**





Reference







SSIM = 0.93







## **SNR dependence**

How should the acceleration factor be chosen as a function of SNR?

SNR DEPENDENCE IDEA OF A MINIMUM INPUT SNR(R,N)



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#### SNR DEPENDENCE EXPERIMENTAL POINTS







## R<sub>max</sub>(ε, Ν, SNR)

# Towards a maximum undersampling factor dependent on image quality threshold $\varepsilon$ , image size *N* and *input SNR*?



We introduce:  $R_{max}(\varepsilon, N, SNR) = max \{ R: SSIM(I; I_{ref}) \ge \varepsilon \}$ 



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## **MR feasible sampling schemes**

Radial golden angle Multiple curve sampling

How do they perform compared to pointwise samples? Can we extend results on iid sampling to MR feasible sampling? II. RESULTS MR FEASIBLE SAMPLING SCHEMES







#### I. Materials and methods

- Simulations
- Experiments

#### II. Results

- Resolution dependence
- SNR dependence
- $R_{max}(N, SNR)$
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#### **III. DISCUSSION AND CONCLUSION**

#### **Compressed Senging in MRI:**

What is the maximum degree of acceleration that can be applied in a given situation?

#### **1)** About resolution dependence

- High resolution → Large subsampling factor
- Quantitative verification
- This tendency is expected to be even stronger for 3D imaging.

#### 2) About SNR impact

- SNR<sub>min</sub> to use a given *R* while preserving desired quality.
- Low SNR occur in high resolution imaging (eg: N=1024)
- High resolution CS-MRI needs to maximize the input SNR:
  - Ultra High Field in MRI
  - → multiple receiver coils.



- 3)  $R_{max}(\varepsilon, N, SNR)$  as a compressed summary
- 4) Results on iid sampling can be extented to MR feasible sampling schemes

lid sampling gives an near upper bound to undersampling performances.

- *x* Some limitations of the study:
  - Reconstruction
    - Other reconstructions may lead to higher image quality
  - Image quality metrics
  - Results could be extented to prospective CS-MRI



# Thanks for your attention! Any questions?

#### APPENDIX EFFECT OF REGULARIZATION PARAMETER





• We wish to acknowledge Michel Bottlaender for the use of the *ex-vivo* baboon brain.