Master of Science in Informatics at Grenoble
Master Mathématiques Informatique - spécialité Informatique
option Graphics Vision and Robotics

Scalable Image Reconstruction Methods for Large Data: Application to Synchrotron CT of Biological Samples

Claude Goubet

Friday May 23rd, 2017

Research project performed at CREATIS

Under the supervision of:
Juan F. P. J. Abascal

Defended before a jury composed of:
Head of the jury
Jury member 1
Jury member 2

June 2017

Abstract

Your abstract goes here...

Acknowledgement

I would like to express my sincere gratitude to .. for his invaluable assistance and comments in reviewing this report... Good luck :)

Résumé

Your abstract in French goes here...

Contents

— 1 —
Introduction

- Context: osteoporose study
- Need: study bone structure in nano scale
- Tool: CT scan in ESRF
- Problem: High dose, change in sample composition, motion, radiations...
- Solution: Use of compress sensing to perform low dose reconstruction
- Problem: not so much work in nano scale and nothing on biological samples
- Proposed methode: iterative TV denoising 2D and 3D. Study the low dose reduction factor with biological sample, and study possibility of extention using 3D TV.
- Plan description

— 2 —
State-of-the-Art

intro about CT and importance for osteoporosis diagnosis + use of SR + low dose problem CS ([?, ?, ?])

2.1 Dose reduction in SR Micro-CT

Multiple CS algorithm were developed for Micro-CT allowing to generate different spacial resolutions. Alternative methods then FBP necessary to recover missing projections. Iterative algorithms are used.

2.1.1 No SR

SART-L1 [?, ?] ASD-POCS TV [?]

2.1.2 CS on SR micro-CT

multiple iterative methods using CGTV ([?]) ART with multiple denoising (TV [?]; L1 minimisation [?]; Discrete packet shrinkage [?]) SART ([?] with TV [?]) OS-SART [?]) EST [?, ?] PCCT [?] define resolution for each solution (maybe more details?)

2.2 SR Nano-CT

Nano-CT general ref: [?] (I can have other references but are mostly about the hardware side, new materials and acquisition methodology, or image post-processing without having used low dose)
less CS reconstruction experimented
Low dose nano OS-SART L1 norm TV [?]

2.3 Wrap-up

A lot of research these past few years of CSCT going toward a improvement of spacial resolution and dose reduction. Yet not so much has been done on Nano scale. In the context of osteoporosis nano scale is mandatory for a accurate diagnosis. Present our objective.

— 3 —
Problem Statement

- what to say else than in intro?

— 4 —

Proposed approach

We propose to use iterative reconstruction with the algorithm described by [**?**]. Split Bregman algorithm gives a solution to an L1-L2 constrained problem. We will here describe the bregman iteration and it's application to L2 minimisation reconstructions which will be used in our algorithm.

4.1 Split Bregman iterative reconstruction

4.1.1 Split Bregman iteration

Using Split Bregman we wish to solve the constrained reconstruction optimization problem described in the section **??**:

$$\min_u ||\nabla_u||_1 \text{ such that } Fu = f \tag{4.1}$$

Such constrained problem problems are difficult to solve directly. For this reason we need to define a new unconstrained problem. Luckily it is possible to approximate (4.1) as:

$$\min_u ||\nabla_u||_1 + \frac{\lambda}{2}||Fu - f||_2^2 \tag{4.2}$$

The Bregman iteration allows us to reduce 4.1 in even shorter unconstrained problems using Bregman distances. These constrained problem can be resolved iteratively as follows:

$$\begin{aligned} u^{k+1} &= \min_u ||\nabla_u||_1 + \frac{\lambda}{2}||Fu - f^k||_2^2 \\ f^{k+1} &= f^k + f - Fu^k \end{aligned} \tag{4.3}$$

4.1.2 L1 regularization problem

Our compressed sensing reconstruction method is based on L1 regulation. A more faithful reconstruction problem must be formulated and we will see how to solve it iteratively with split Bregman.
The idea is to "de-couple" the L1 and L2 parts of our original problem. We wish to minimize the Total Variation ∇_u of the image and a weight function $H()$. We write the problem as follows:

$$\min_{u,d} ||d||_1 + H(u) \text{such that} d = \nabla_u \tag{4.4}$$

Which can be computed iteratively using Split Bregman iteration as:

$$\begin{aligned}(u^{k+1}, d^{k+1}) &= \min_{u,d} ||d||_1 + H(u) + \frac{\lambda}{2}||d - \nabla_u - b^k||_2^2 \\ b^{k+1} &= b^k + \nabla_{u^{k+1}} - d^{k+1}\end{aligned} \tag{4.5}$$

4.2 SB-TV-2D reconstruction

isotropic TV denoising pbl:

$$\min_u ||\nabla_u||_1 \text{ such that } ||Fu - f||_2^2 < \sigma^2 \tag{4.6}$$

where $\nabla_u = (\nabla_x, \nabla_y)u$, f represents the projection space, F the projection operator, u the image domain and σ represents the variance of the signal noise.

$$\begin{aligned}u^{k+1} &= \min_u ||\nabla_u||_1 + \frac{\lambda}{2}||Fu - f^k||_2^2 \\ f^{k+1} &= f^k + f - F_u^k\end{aligned} \tag{4.7}$$

We fall here into an unconstrained problem which is not steight forwardly solved. In order to get a constrained problem we will insert a variable d such that $d = \nabla_u$.
We can now use the Split Bregman iteration in order to solve our new problem:

$$\begin{aligned}u^{k+1} &= \min_{u,d} ||d||_1 + \frac{\lambda}{2}||Fu - f^k||_2^2 \text{ such that } d = \nabla_u \\ f^{k+1} &= f^k + f - F_u^k\end{aligned} \tag{4.8}$$

And get to a solution where L1 and L2 elements of our original problem are spleted into two equations:

$$\begin{aligned}u^{k+1} &= \min_u \frac{\mu}{2}||Fu - f^k||_2^2 + \frac{\lambda}{2}||d^k - \nabla_u - b^k||_2^2 \\ d^{k+1} &= \min_u ||d||_1 + \frac{\lambda}{2}||d - \nabla_u - b^k||_2^2 \\ b^{k+1} &= b^k + \nabla_u^{k+1} - d^{k+1} \\ f^{k+1} &= f^k + f - F_u^k\end{aligned} \tag{4.9}$$

Now is left to sole the minimization on the u^{k+1} and d^{k+1} operations. **Solution for u**
The definition of u^{k+1} in 4.9 is differentiable. We can hence get the minimum using the derivative. We the get:

$$(\mu F^T F + \lambda \nabla^T \nabla)u^{k+1} = \mu F^T f^k + \lambda \nabla^T (d_x^k - b_x^k) K u^{k+1} = rhs^k \tag{4.10}$$

Solution for d
The expression of d^{k+1} in 4.9 is not coiples. Hence the solution will be computed thanks to the shrinkage thresholding function:

$$shrink(x, \gamma) = \frac{x}{|x|} \times max(|x| - \gamma, 0) \tag{4.11}$$

so that:

$$d^{k+1} = shrink(\nabla_u^{k+1} + b^k, 1/\lambda) \tag{4.12}$$

4.3 SB-TV-3D

pbl: $\alpha||(\nabla_x, \nabla_y, \nabla_z)u||_1$such that$||Fu - f||_2^2 < \delta^2$

$$\begin{aligned} u &= \\ d &= \end{aligned} \tag{4.13}$$

— 5 —
Method evaluation

- show images compare to FBP
- computation time
- error rates
- 2D vs 3D better? worst? why?

— 6 —
Conclusion

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem. Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

— A —

Appendix

Appendix goes here...