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

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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

Write this chapter LAST. Should be 5 to 10 pages. This chapter provides a quick summary of the essential contents of the research project, principal results and contents of the report. The target audience is members of the jury who do NOT have time to completely read all 21 reports, as well academic members of other juries who wish to compare this work to other works.

1.1 Background

This is a generic title. Replace it with an actual title that describes the context of the work. Short $1/2$ *page summary of the technological context of the work and why it is interesting or important*

- Osteoporosis study
- Need to study nano scale bone structure
- Nano CT scan in ESRF

1.2 Problem Statement

This is a generic title. Replace it with an actual title that describes the context of the work. Approx Â½ to 1 page description of the research problems that was addressed and what was required to address it.

- High radiation dose $->$ changing sample composition, sample motion...
- Need to use compress sensing for low dose reconstruction, not so much done in nano scale and on biological samples

1.3 Scientific Approach and Investigative Method and Results

This is a generic title. Replace it with an actual title that describes the context of the work. Approx 1 to 2 page description of the scientific approach or approaches to a solution and how it was investigated and evaluated. Present a summary of the principal results obtained.

- Use of iterative reconstruction methods, presentation of SB-TV-2D, SB-TV-3D
- Evaluation : metrics description (metrics proposed in 2nd meeting) (mean squared error, psnr, SIFT detection? All in 3D, 2D (xy, yz, xz))
- Description of main results

1.4 Contents of this report

Approx Â½ page per chapter. Summarize the contents of the subsections of each chapter. Give the topics addressed and summarize what is written in each chapter.

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2 Problem Statement, Analysis and State of the Art

This is a generic title. Replace it with an actual title that describes the context of the work. Give a clear statement of the research problem, and the current scientific state of the art on this problem. USe the state of the art to analyse the problem. Use the analysis to develop a proposal for a possible solution to the problem (or multiple possible solutions).

2.1 Problem Statement

- Goal: isotropic resolution of 10 nm
- Technical constraints in radiation dose and data size
- Problem: dose reduction implies reconstruction from less data: compressed sensing

2.2 State of the Art

intro about CT and importance for osteoporosis diagnosis + use of SR + low dose problem CS ([3, 1, 11])

2.2.1 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.

No SR

SART-L1 [18, 16] ASD-POCS TV [7]

CS on SR micro-CT

multiple iterative methods using CGTV ([17]) ART with multiple denoising (TV [15]; L1 minimisation [9]; Discrete packet shrinkage [14]) SART ([12] with TV [13]) OS-SART [8]) EST [4, 19] PCCT [5] define resolution for each solution (maybe more details?)

2.2.2 SR Nano-CT

Nano-CT general ref: [2] (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 [10]

2.2.3 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.

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Theoretical Foundations for the Solution

This is a generic title. Replace it with an actual title that describes the context of the work. Describe in abstract (theoretical) terms how the proposed approach can be implemented and how to solve related sub problems. Use the state of the art as an analysis tool.

3.1 Computational Tomography

- brief descrition of basics of CT reconstrution, (projections, retro projections...)

3.2 Syncrothron Radiation Nano-CT reconstruction

- brief mention of phase retriavle, Max thesis
- Description of tomographique reconstruction (focus on, apply CS)

3.3 Compressed sensing

- ref to original work
- CS in nano CT: iterative SB reconstruction

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Practical implementation

This is a generic title. Replace it with an actual title that describes the context of the work. Give a concrete discussion of how the proposed solution was (or could be) implemented or evaluated.

4.1 Compressed Sensing Formulation

- formulation of the compressed sensing equation $Fu = d$

4.2 Split Bregman iterative reconstruction

We propose to use iterative reconstruction with the algorithm described by [6]. 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.

4.2.1 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:

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

4.2.2 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:

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

4.3 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:

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

4.4 SB-TV-3D

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

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

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Experimental Performance Evaluation or validation of solution

This is a generic title. Replace it with an actual title that describes the context of the work. Describe the performance metrics, experimental hypotheses, experimental conditions, test data, and expected results. Provide the test data. Interpret the results of the experiments. Pay special attention to cases where the experiments give no information or did not come out as expected. Draw lessons and conclusions from the experiments. Explain how additional experiments could validate or confirm results.

- show images compare to FBP
- computation time
- error rates
- compare corronal sagital and axial views
- 3D not as good as expected? Why? How to make ferther tests to understand why?

— 6 —
Discussion of Results

This is a generic title. Replace it with an actual title that describes the context of the work. Discussion lessons learned from the experiments, and new problems that are raised.

- Discuss results and compare to previous work
- Technical issues and limitations

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Summary of results, Conclusions, Expected Impact

This is a generic title. Replace it with an actual title that describes the context of the work. Give a summary of the problem, approach, implementation and evaluation. Discuss the principal results in abstract terms. Discuss expected impact and further research directions. Explain how the project satisfies the evaluation criteria for a Masters Research project.

- State Goals
- sumary of results
- Further work
- Conclusion (final phrase + impact (may be use in ESRF?))

— A —
Appendix

Appendix goes here...

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