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

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Defended before a jury composed of:
James Crowley
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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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 analyze 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: Microscopic imaging technique; isotropic resolution of 10 nm the theoretical limit.
- Current: State of the art beam-line ID16 [18] with a lateral spacial resolution around 50 nm, using an energy range of 5 to 70 KeV. Not yet evaluated for bones.
- Two axis in nano-CT : Phase retrieval and image reconstruction. We will focus in this thesis on the image reconstruction, the phase retrieval phase retrieval was answered by [10]
- Technical constraints in radiation dose and time constraint, 3000 projections takes multiple hours to acquire. High dose and long exposition causes the sample to change its composition.
- Problem: dose reduction implies reconstruction from less data: compressed sensing

2.2 Introduction to Low Dose CT

intro about CT and importance for osteoporosis diagnosis + use of SR + low dose problem CS ([5, 2, 14])

2.2.1 Dose reduction in Micro-CT

Multiple CS algorithm were developed for Micro-CT. In respect to the ALARP principle which aims to keep the radiation doses "As Low As Reasonably practicable" and in order to reduce the acquisition time and effect on the sample Alternative reconstruction methods for FBP are necessary. These methods need to be able to reduce the number of projections used for the reconstruction, without affecting the output image quality. Iterative regularized algorithms are used.
Studies of alternative clinical CT reconstruction are review by Pan et al. in [21]. Our focus is on Synchrothron Radiation computational tomography (SR-CT) image reconstruction with less projection. One commonly used method for data reduction is Compressed Sensin (CS). First proposed by Candes et al in 2006 [3] it has been used since in many Signal Processing Fields. CS techniques have been developed for tomography such as Split-Bregman reconstruction [8] used by Abascal et al. for Fluorescence diffuse optical tomography [1]. But in particular CS has been used in Micro-CT.

CS on SR micro-CT

multiple iterative methods using CGTV ([23]) ART with multiple denoising (TV [20]; L1 minimisation [12]; Discrete packet shrinkage [19]) SART ([15] with TV [17]) OS-SART [9]) EST [6, 24] PCCT [7] define resolution for each solution (maybe more details?)

2.2.2 SR Nano-CT

Few research has been done yet in Nano-CT. Most of them focus on the Phase Retrieval such as Langer who reconstructed images in a spacial resolution of 120-150 nm [11]. Nano-CT general ref: [4] less CS reconstruction experimented
The little research on Low dose nano concerns the OS-SART L1 norm TV algorithm [13] not experimented on bone data

2.3 Proposed solution to dose reduction

If a state of the art acquisition allows to reconstruct images with a spacial resolution of 50 nm at the ESRF, no studies have been done on the feasibility of using of compressed sensing for bone SR-CT. We propose here to use split bregman algorithm for compressed sensing to reduce the number of projection.

— 3 —

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, Define Radon Transform
- show an image and output sinogram explain...

3.2 Syncrothron Radiation Nano-CT reconstruction

- brief mention of phase retrieval, Max thesis
- Wave monochromatique incoherent
- 1 formula refractive index
- Attenuation: wave/shift
- Description of tomographic reconstruction (focus on, apply CS)

3.3 Compressed sensing

- Candes more details that state of the art
- CS in nano CT: iterative SB reconstruction proposed (Juan ART-TV SB, Pesquet Scalable splitting)

— 4 —
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.

explain method to validate low dose / LD protocol / Acquisition

4.1 Compressed Sensing Formulation

$$\min_u ||Wu||_1 st Fu = f$$

3 conditions: u sparce, Wu ..., incoherence.
u sparce in domain W
CS in $||Wu||_p$ with $p \leq 1$ -> Bone details, $p \leq 1$ preserves borders.
TV non differentiable: $(TV)' = \frac{1}{\nabla u}$

4.2 Split Bregman iterative reconstruction

We propose to use iterative reconstruction with the algorithm described by [8]. Split Bregman algorithm gives a solution to an L1 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 **??** and set $W = \nabla$ as it has been shown to be efficient:

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

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 and gradient. It is hence difficult to minimize. A splitting technique 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 $H()$. Splitting can be done by introducing new variable and define a new constraint:

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

Using Bregman on it again we get other problems that can be splitted:

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

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

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

4.5 Scalability

- ESRF -> Cluster, method, call projection, retro-projection explain what to change where in the algorithm

— 5 —

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.

5.1 Hypothesis

- CS can be used to preserve image quality
- Can reduce dose and make a scalable algorithm
- SB can be implemented at ESRF
- Can use it on Bone data

5.2 Data-set description

Data characteristics

Parameters defining the projection file format

- number of projections: 2000
- image dimensions: 2048×20148
- vertical and horizontal pixel size: 0.119865 microns

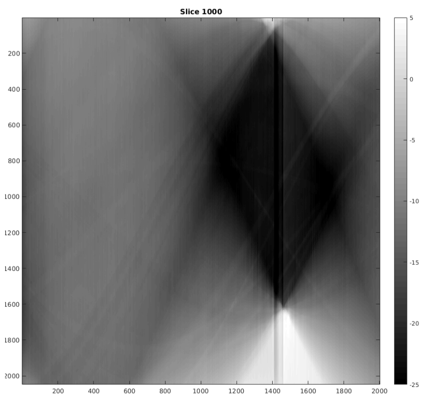
Parameters defining experiment

- angle between projections: 0.09 degree
- Vertical rotation axis position: 1024.006591 pixel
- energy: 33.6

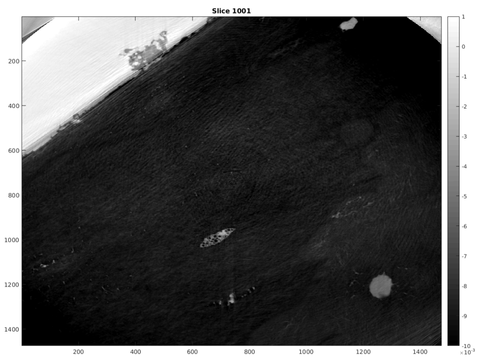
Parameters defining reconstruction

- start voxel: (1,1,1) end voxel (2048, 2048, 256) of reconstruction volume
- Optic used: 0.119865
- Pad method: reflect
- number of planes: 4
- number of angles: 645
- Rotation axis

5.2.1 Sinograms and reconstruction



(a) One slice sinogram



(b) One slice reconstruction

Figure 5.1 – one slice of the 3D Micro SR-CT data used for the experiment

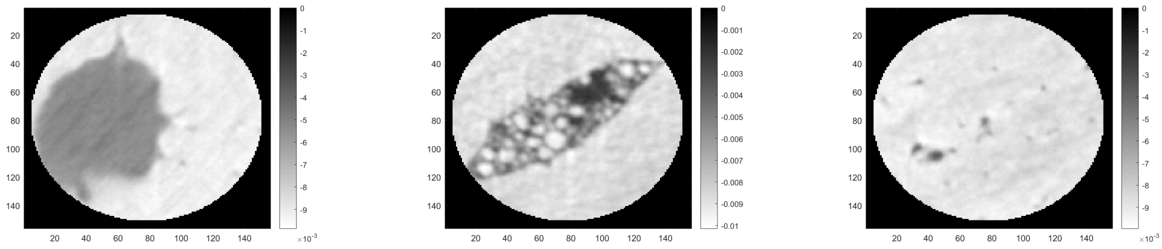
5.3 Experiments description

5.3.1 Truncated images

5.3.2 Tunning of parameters

5.3.3 Scenarios

Scenarios of Low dose on different targets were defined. The number of projections ranges from $1/2$ to $1/10$ of the number required for fully projected reconstruction. An acquisition is considered fully projected when it generates $\pi/2$ times the image size projections.



(a) Target 1 (b) Target 2 (c) Target 3

Figure 5.2 – Targets used for the Matlab experiments

In our case we performed reconstruction with $1/2$, $1/4$, $1/7$ and $1/10$ of the projections. Knowing that our target images were of size 156×156 we used 125, 63, 36, 25 projections displayed in Figure
These reconstructions were performed using FBP, SB-TV-2D and SB-TV-3D.

5.4 Results

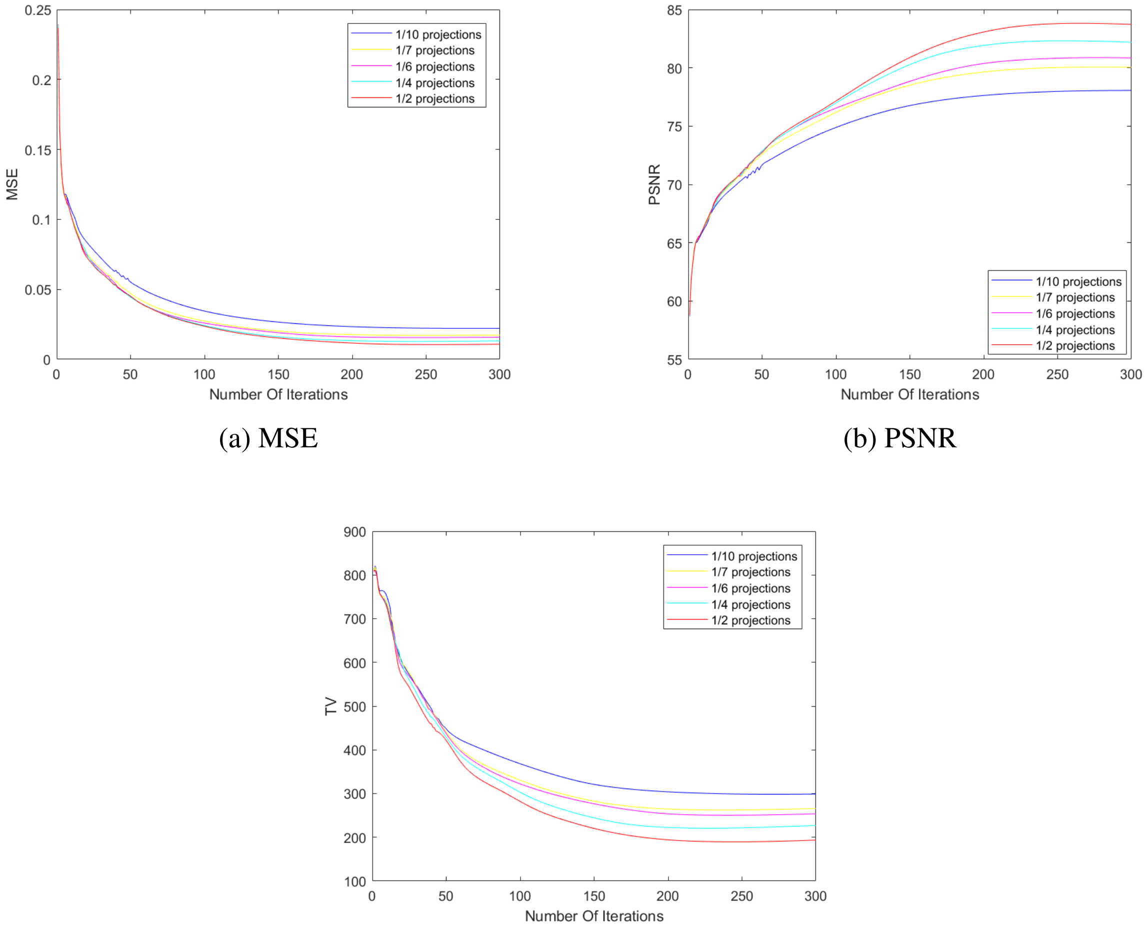
These algorithms will be evaluated in terms of convergence of errors, visual comparison as well as the preservation of Edges and feature points of the resulted reconstructed image.
The errors are expressed in terms of mean squared error (MSE), peak signal to noise ration (PSNR) and total variation (TV), computed between the target image and the reconstructed image.
The Edge preservation will be evaluated in terms of total variation between the canny edge detection between the reference Target image and the reconstructed image.
The feature points were computed using SIFT algorithm for Scale-Invariant Transform Feature detection and description [16]. We decided to use SIFT algorithm because it is shift invariant and we noticed that if some edges were preserved, the smoothing imposed by the SB-TV reconstruction imposed some small shifting which can influence the total variation. Also it allows to display the eventual confusion of a post processing using edges in a intuitive way. The implementation of SIFT was performed by Vedaldi in matlab [22].

5.4.1 Error convergence

FBP

number of projections	**1/2**	**1/4**	**1/7**	**1/10**
MSE	6%	7%	9%	11%
PSNR	67.90	66.92	64.17	62.21
TV	5.70	8.44	14.17	17.95

Table 5.1 – FBP Errors on Target 1



(a) MSE (b) PSNR

(c) TV

Figure 5.3 – SB-TV-2D errors on Target 1

SB-TV-2D

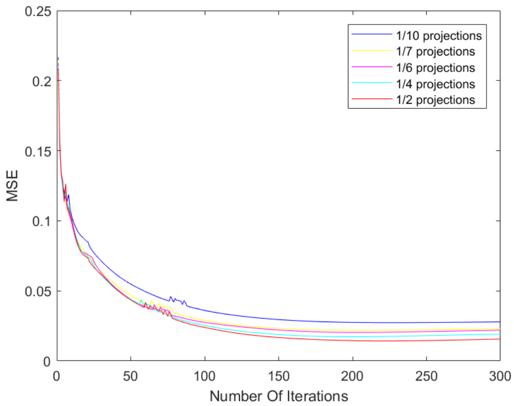
SB-TV-3D

5.4.2 Visual comparison

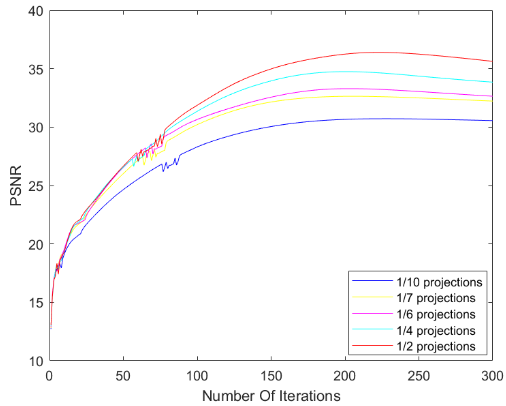
5.4.3 Edges preservation

5.4.4 Feature points preservation

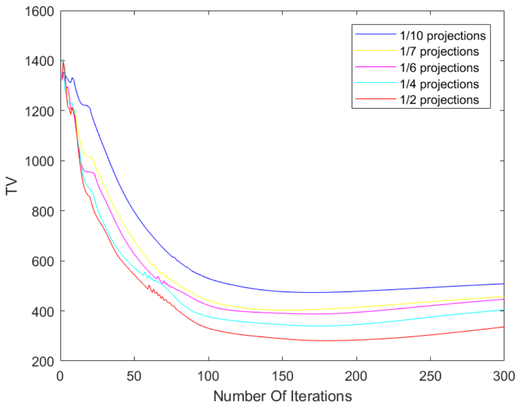
- show images compare to FBP
- computation time
- error rates
- compare corronal sagital and axial views
- 3D not as good as expected? Why? How to make ferther tests to understand why?



(a) MSE

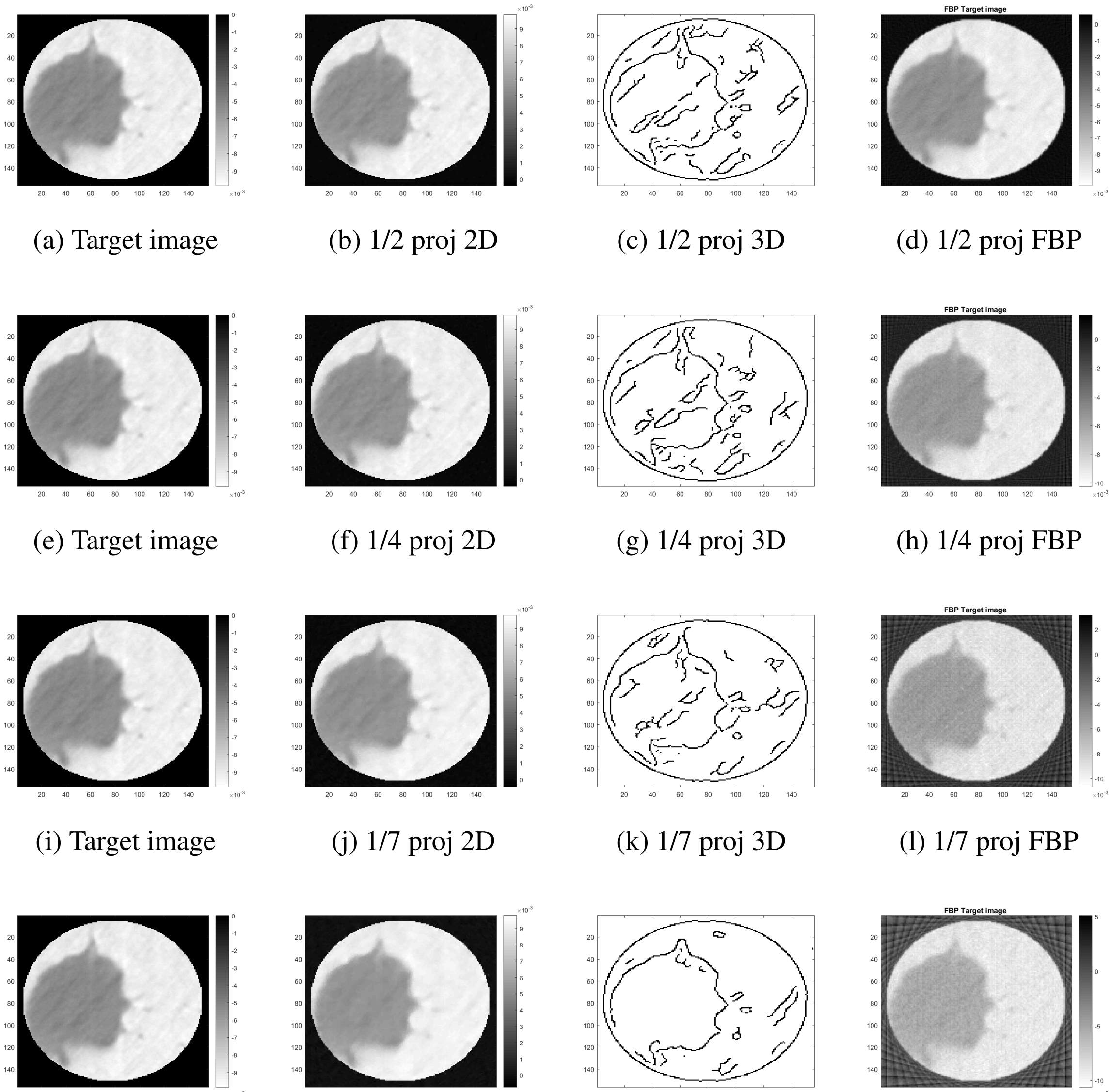


(b) PSNR



(c) TV

Figure 5.4 – SB-TV-3D errors on Target 1



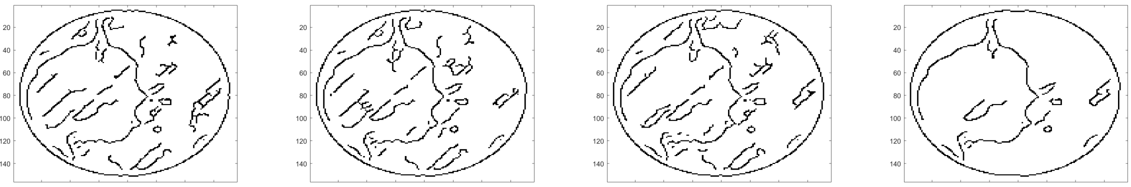
(a) Target image (b) 1/2 proj 2D (c) 1/2 proj 3D (d) 1/2 proj FBP

(e) Target image (f) 1/4 proj 2D (g) 1/4 proj 3D (h) 1/4 proj FBP

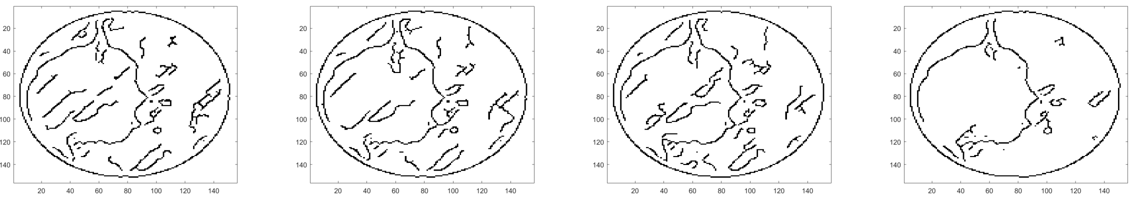
(i) Target image (j) 1/7 proj 2D (k) 1/7 proj 3D (l) 1/7 proj FBP

(m) Target image (n) 1/10 proj 2D (o) 1/10 proj 3D (p) 1/10 proj FBP

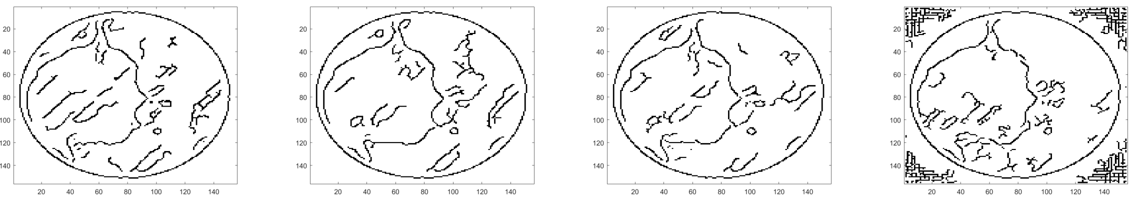
Figure 5.5 – Canny edge detection



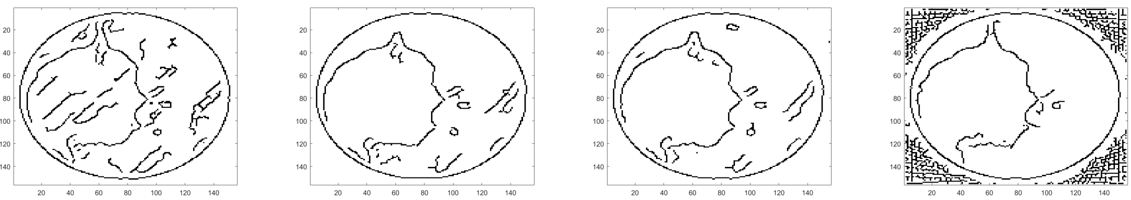
(a) Target image (b) 1/2 proj 2D (c) 1/2 proj 3D (d) 1/2 proj FBP



(e) Target image (f) 1/4 proj 2D (g) 1/4 proj 3D (h) 1/4 proj FBP



(i) Target image (j) 1/7 proj 2D (k) 1/7 proj 3D (l) 1/7 proj FBP



(m) Target image (n) 1/10 proj 2D (o) 1/10 proj 3D (p) 1/10 proj FBP

Figure 5.6 – Canny edge detection

— 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

— 7 —

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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