# Project technical report 2: Split Bregman

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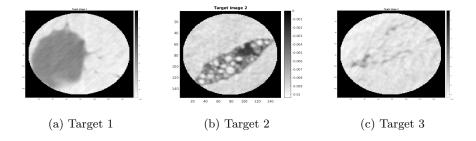
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## 1 2D Split Bregman

#### 1.1 Scenarios description

#### 1.1.1 image samples

In order to reduce computation time for the comparison of scenarios and methods three sample images were selected. These sample are all 156\*156 images representing relevant details that we wish to preserve from the full-size image.



#### 1.1.2 scenarios

We defined multiple scenarios in order to test the algorithms.

- We evaluate sequentially each target
- For each target we perform SB-TV on different number of iterations (20, 100, 200, 1000, 5000, 10000) (5000 and 10000 currently computing, I will change the code so that we save all these images in one call and not one call for each number of iterations)
- For each iteration number we perform SB-TV on different doses (100%, 50%, 25% and 10% of projection) (100% projections being the image size).

Future scenarios will be perform with noisy projections.

#### 1.2 Image sample 1

#### 1.2.1 Fully projected (image size #proj)

Use of 156 projections. We are here comparing the number of iterations of Split Bregman algorithm to the target and FBP images (respectively Figure 12a and 2b. in Figure 13 are displayed 20, 200, 1000 and 5000 iterations.

We can notice that the number of edges recovered increases with the number of iterations.

In the next sections we will use 5000 iterations since it corresponds to the best image recovery. Some evaluation metrics are displayed in Table 2

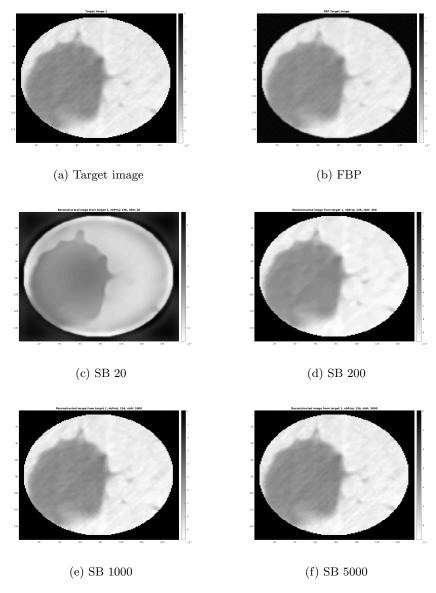


Figure 2: Retro-projections on fully projected object

reconstruction	FBP	SB 5000	SB 1000	SB 200	SB 100	SB 20
Error	0.06	0.006	0.0081	0.0132	0.0244	0.1065
Time exec		11.96	62.45	129.66	647.87	3314

Table 1: Reconstruction error rate from target image

# ${\bf 1.2.2}\quad {\bf Sample~1~Low-Dose~reconstruction}$ reconstructed images

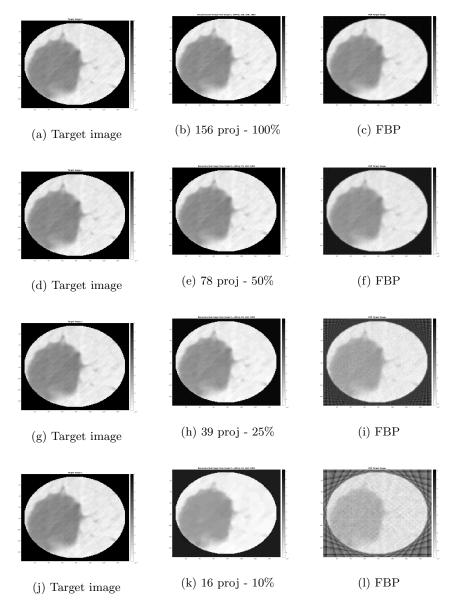


Figure 3: Retro-projections on fully projected object

#### 1.2.3 Error evaluation

in this section we wish to visualize and compare loss of information between Low-Dose SB-TV and FBP as well as define a metric allowing to evaluate the amount of information preserved.

Multiple approaches are proposed.

Table 2 regroup error evaluations such as normalized variation between reconstructed image and target image. In both of these metrics SB-TV get better results. Although, these methods of error evaluation are less sensitive to noise induced by TV minimization and hence might not be ideal.

Peak signal to noise ratio was also evaluated in Table 2. This metric is usually used to measure the compression level of an image compared to a target. Using this method, SB-TV appear to be of a worst quality than FBP. formula:

$$PSNR = 10 \times log_10 \left(\frac{MAX_I^2}{MSE}\right)$$

Loss of contrast is displayed in Figure 7. This Figure 7a represents the middle line of FBP reconstruction with different doses when Figure 7b represent SB-TV mid lines. We can notice that FBP preserves the contrast while reducing the number of projections, but results in a noisier signal as the number of projection decrees. SB-TV induces loss of contrast but results in a less noisy signal.

We also estimated that one way of evaluating the loss of information would be to work on image edges. To do so we compared canny edge detection on every projections (Figure 4). By applying a threshold of 10% on the edge detection we were able to isolate the relevant details (Figure 5). TV of edges detection between target image and reconstructed image is displayed in Table 2.

The TV of edges is higher that the TV of images by a factor of 10<sup>3</sup>. Although SB-TV has better results. This gap between image and edges variation come from the fact that edges are shifted between doses even though the information is still there. On idea was then to evaluated the similarities between the images and egdes usinf SIFT descriptor.

SIFT descriptor is scale, rotation and shift invariant. Hence even shifted information will be retrieved and matched to the target image. Figure 8 represent SIFT recognition on the images and Figure 9 represent SIFT on edges.

Table 3 and 4 show that SB-TV preserves more features than FBP which has more confused feature matching.

## Canny edges detection

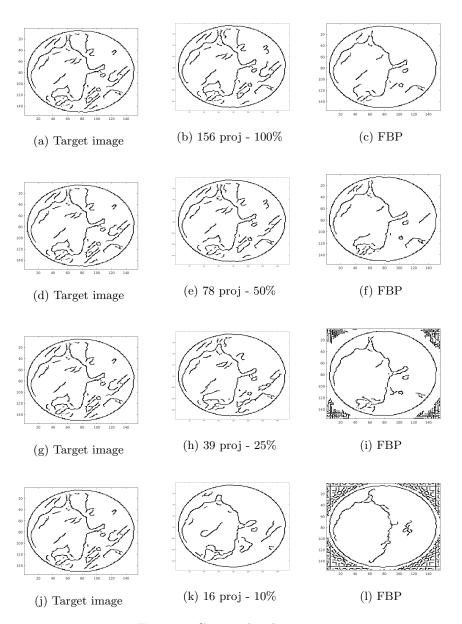


Figure 4: Canny edge detection

#### Thresolded Canny edges detection

The aim to simulate a segmentation. The threshold used is 10%.

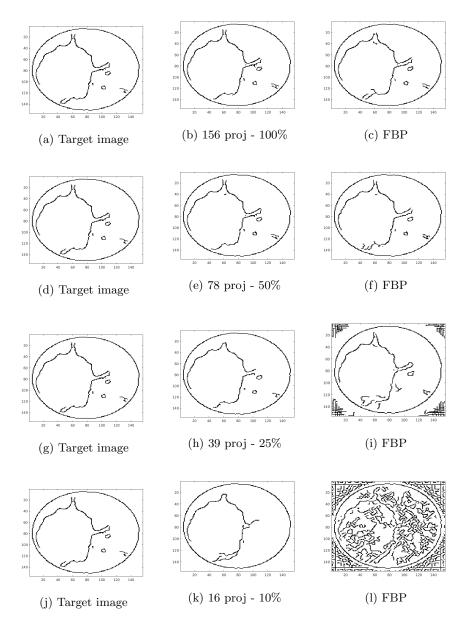


Figure 5: Canny edge detection with threshold of 10%

#### Errors table

reconstruction	156 Proj (100%)	78 Proj (50%)	39 Proj (25%)	16 Proj (10%)
FBP	$6.00_{e^{-2}}$	$6.40_{e^{-2}}$	$8.40_{e^{-2}}$	$1.86_{e^{-2}}$
SB 1000	$0.81_{e^{-2}}$	$0.87_{e^{-2}}$	$1.24_{e^{-2}}$	$2.36_{e^{-2}}$
FBP-PSNR	68.00	67.45	65.16	58.27
SB-PSNR	85.54	84.84	84.8381	76.20
FBP-TV	5.21	6.94	11.71	28.55
SB-TV	0.91	1.01	1.40	2.07
FBP-TV-Edges	$1.115_{e^{+03}}$	$1.177_{e^{+03}}$	$2.506_{e^{+03}}$	$4.259e^{+03}$
SB-TV-Edges	$0.378_{e^{+03}}$	$0.529_{e^{+03}}$	$1.316_{e^{+03}}$	$1.969e^{+03}$

Table 2: Reconstruction error rate from target image

#### Contrast loss evaluation

Looking at Figure 7 we see that Low-Dose FBP preserves the contrast but adds noise. When Low-Dose SBTV reconstruction is less noisy but loses contrast.

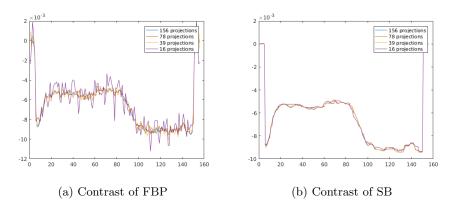
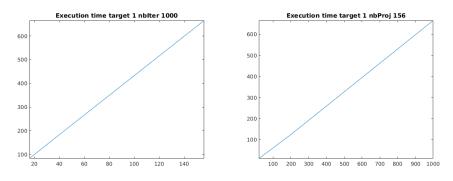


Figure 6: Contrast of the middle line of sample 1

#### Execution time



(a) Execution time: i number of projec- (b) Execution time: i number of iterations, tion, j seconds for 1000 iterations j seconds for 156 projections (100%)

Figure 7: Execution time of sample 1 156\*156 image

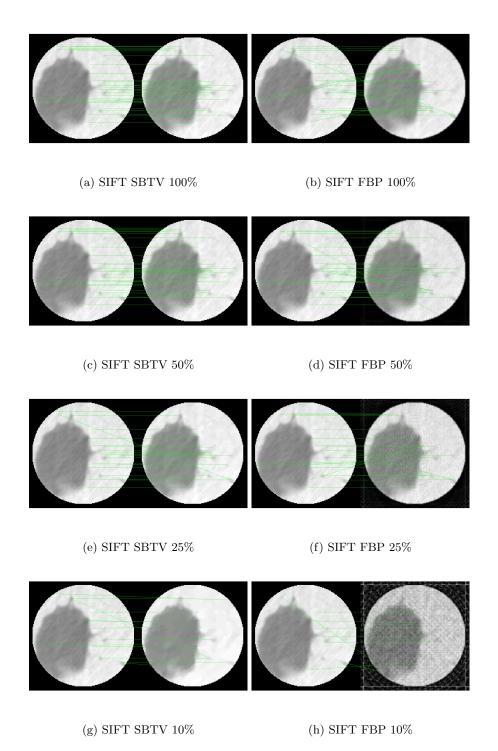


Figure 8: SIFT image matching between target and reconstructed images

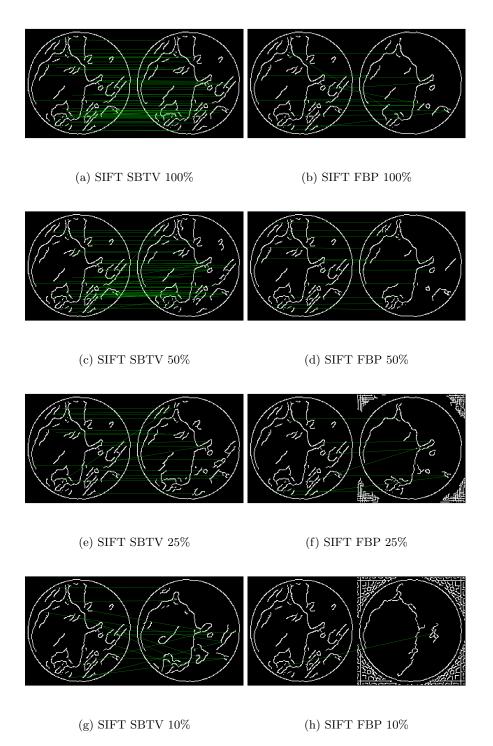


Figure 9: SIFT image matching between target and reconstructed images edges

reconstruction	matches	FP	Reconstuction	matches	FP
SB 100%	37	2 (5.41%)	FBP 100%	28	6 (21.43%)
SB 50%	37	1 (2.70%)	FBP 50%	32	3 (9.38%)
SB 25%	24	1 (4.17%)	FBP 25%	23	4 (17.39%)
SB 10 %	13	3 (23.08%)	FBP 10%	8	3 (37.50%)

Table 3: SIFT image matching

reconstruction	matches	FP	Reconstuction	matches	FP
SB 100%	72	4 (5.56%)	FBP 100%	16	4 (25%)
SB 50%	52	6 (11.54%)	FBP 50%	13	1 (7,69%)
SB 25%	22	2 (9.09%)	FBP 25%	8	3 (37.5%)
SB 10 %	14	8 (57,14%)	FBP 10%	1	1 (100%)

Table 4: SIFT Edges matching

## 1.3 Image sample 2

## 1.3.1 Fully projected

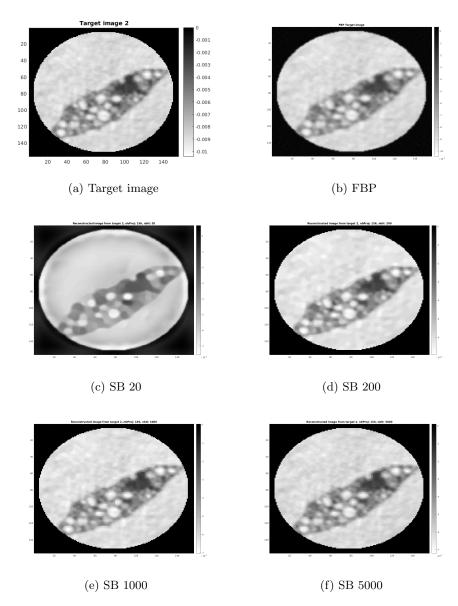


Figure 10: Retro-projections on fully projected object

reconstruction	FBP	SB 5000	SB 1000	SB 200	SB 100	SB 20
Error	0.058	0.0116	0.0124	0.0176	0.0292	0.1059
Time exec		11.96	62.45	129.66	647.87	3314

Table 5: Reconstruction error rate from target image

#### 1.3.2 Sample 2 Low-Dose reconstruction

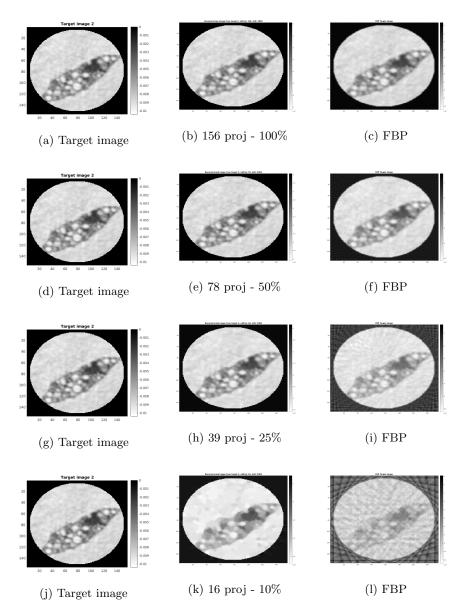


Figure 11: Retro-projections on fully projected object

reconstruction	156 Proj (100%)	78 Proj (50%)	39 Proj (25%)	16 Proj (10%)
FBP	0.058	0.062	0.084	0.200
SB 5000	0.012	0.013	0.019	0.049

Table 6: Reconstruction error rate from target image

## 1.4 Image sample 3

## 1.4.1 Fully projected (image size #proj)

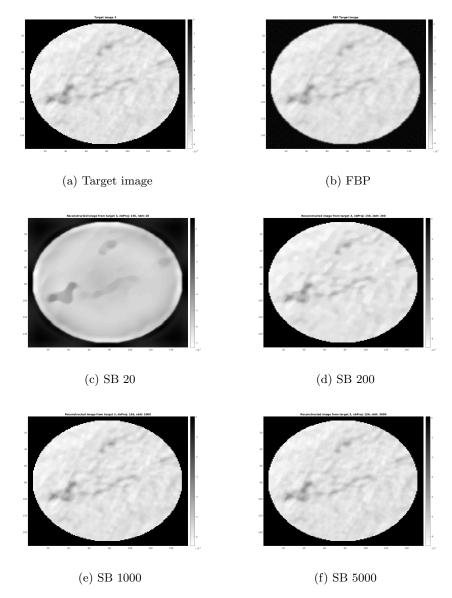


Figure 12: Retro-projections on fully projected object

reconstruction	FBP	SB 5000	SB 1000	SB 200	SB 100	SB 20
Error	0.0561	0.0055	0.0075	0.0139	0.0252	0.0878
Time exec		11.96	62.45	129.66	647.87	3314

Table 7: Reconstruction error rate from target image

#### 1.4.2 Sample 3 Low-Dose reconstruction

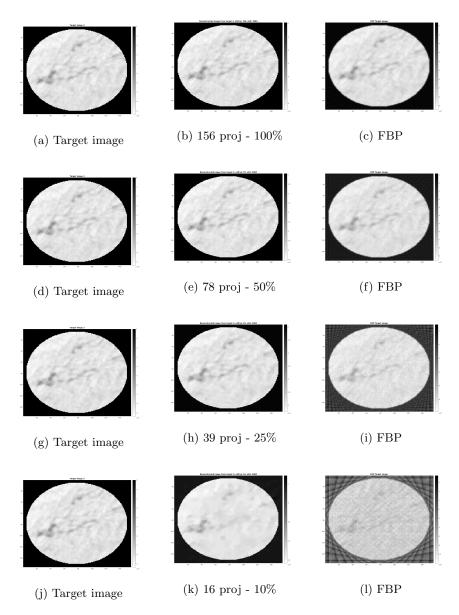


Figure 13: Retro-projections on fully projected object

reconstruction	156 Proj (100%)	78 Proj (50%)	39 Proj (25%)	16 Proj (10%)
FBP	0.0561	0.0595	0.0779	0.1737
SB 5000	0.0055	0.0072	0.0135	0.0287

Table 8: Reconstruction error rate from target image

## 2 Questions

- Which noise model to add to images?
- Which segmentation/post processing will be done on the reconstructed data? (to target accurate metrics)