

# Matlab Imaging Algorithms: Image Reconstruction, Restoration, and Alignment, with a Focus in Tomography. (Version 2.4)

Toby Sanders  
email: toby.sanders@asu.edu  
School of Mathematical and Statistical Sciences,  
Arizona State University, Tempe, AZ.

## Abstract

This document is a guide for several MATLAB imaging code, which can be used for image reconstruction, denoising, alignment, etc. There is a general focus on tomographic reconstruction and alignment, as well as  $\ell_1$  regularization algorithms.

## Contents

<b>1</b>	<b>Solvers for Signal, Image, and Volume Reconstruction</b>	<b>1</b>
1.1	Higher order TV based $\ell_1$ Regularization . . . . .	1
1.2	HOTV based $\ell_1$ - $\ell_1$ Regularization . . . . .	4
1.3	General $\ell_1$ regularization algorithm . . . . .	4
1.4	HOTV $\ell_2$ Tikhonov Regularization . . . . .	6
1.5	Tomographic reconstruction with SIRT . . . . .	6
1.6	Discrete tomographic reconstruction with DART . . . . .	7
<b>2</b>	<b>Image Alignment</b>	<b>7</b>
2.1	Basic Cross Correlation . . . . .	7
2.2	Center of mass alignment for tilt series alignment . . . . .	8
<b>3</b>	<b>Other utilities and codes potentially of interest</b>	<b>10</b>

## 1 Solvers for Signal, Image, and Volume Reconstruction

### 1.1 Higher order TV based $\ell_1$ Regularization

- **Code name:** HOTV3D
- **Demos:** see demo\_L1optimization\_simple.m, demo\_tomo.m, demo\_MHOTV.m, demo\_inpaint.m, and demo\_1D\_L1.m
- **References:** [2, 5, 4, 1, 3]
- **Description:** An iterative solver for higher order total variation  $\ell_1$  regularization minimization for inverse problems and denoising. That is given a data vector  $b$ , a map  $A$  that maps the unknown signal  $f$  to  $b$ , the algorithm seeks to find

$$\min_f \frac{\mu}{2} \|Af - b\|_2^2 + \|D^k f\|_1$$

MATLAB comments:

```
% Modifications by Toby Sanders @ASU
% School of Math & Stat Sciences
% Last update: 11/01/2018
%
%
% This code has been modified to solve l1 penalty problems with
% higher order TV operators. Several small bugs and notation
% changes have been made as well.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Problem Description %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% function [U, out] = HOTV3D(A,b,n,opts)
%
% Motivation is to find:
%
% min_f { mu/2*||Au - b||_2^2 + ||D^k u||_1 }
%
% where D^k is kth order finite difference.
% Multiscale finite differences D^k can also be used.
% To see how to modify these settings read the file "check_HOTV_opts.m"
%
% The problem is modified using variable splitting and this algorithm
% works with the following augmented Lagrangian function:
%
% min_{u,w} {mu/2 ||Au - b||_2^2 + beta/2 ||D^k u - w ||_2^2
%           + ||w||_1 - (delta , Au - b ) - (sigma , D^k u - w) }
%
% delta and sigma are Lagrange multipliers
% Algorithm uses alternating direction minimization over f and w.
% by default delta = 0.
%
% This algorithm was originally authored by Chengbo Li at Rice University
% as a TV solver called TVAL3.
% original code and description can be found here:
% http://www.caam.rice.edu/~optimization/L1/TVAL3/
%
% Inputs:
% A: matrix operator as either a matrix or function handle
% b: data values in vector form
% n: image/ signal dimensions in vector format
% opts: structure containing input parameters,
%       see function check_HOTV_opts.m for these
%
% Outputs:
% U: reconstructed signal
% out: output numerics
```

- **Important fields in the opts structure:**

**mu** ..... primary parameter balancing the data and regularization terms.

**order** ..... order (k) of the finite difference operator used in the regularization term, can be set to any real number  $\geq 0$ . Generally recommended between 1 and 3.

**levels** ..... Set to an integer generally between 1 and 4. For values greater than 1 a multiscale regularization approach is implemented [5], which is similar to using wavelets.

**scale\_A** ..... set to true or false. This option rescales  $A$  and  $b$  by dividing by the  $\ell_2$  norm of  $A$ , which one may find greatly simplifies the selection of  $\mu$ . Generally recommended to set to true (default).

**scale\_mu** ..... set to true or false. Similar to the "scale\_A" option,  $\mu$  may also be scaled based on the magnitude of  $b$ .

**L1type** ..... set to 'isotropic' to solve the isotropic model or 'anisotropic' to solve the anisotropic model. Isotropic is generally preferred.

**iter** ..... maximum number of total iterations

**tol** ..... convergence tolerance to terminate the algorithm and return the solution

**nonneg** ..... if set to true, problem is solved under the constraint  $f \geq 0$

**wrap\_shrink** ... set to false unless signal is periodic.

*\* Other options are available, a full description of each is given in the "check\_HOTV\_opts.m" file. It is generally recommended to just use default values.*

*\*For automatic HOTV reconstruction of tomographic data see the code HOTV3D\_tomo.m.*

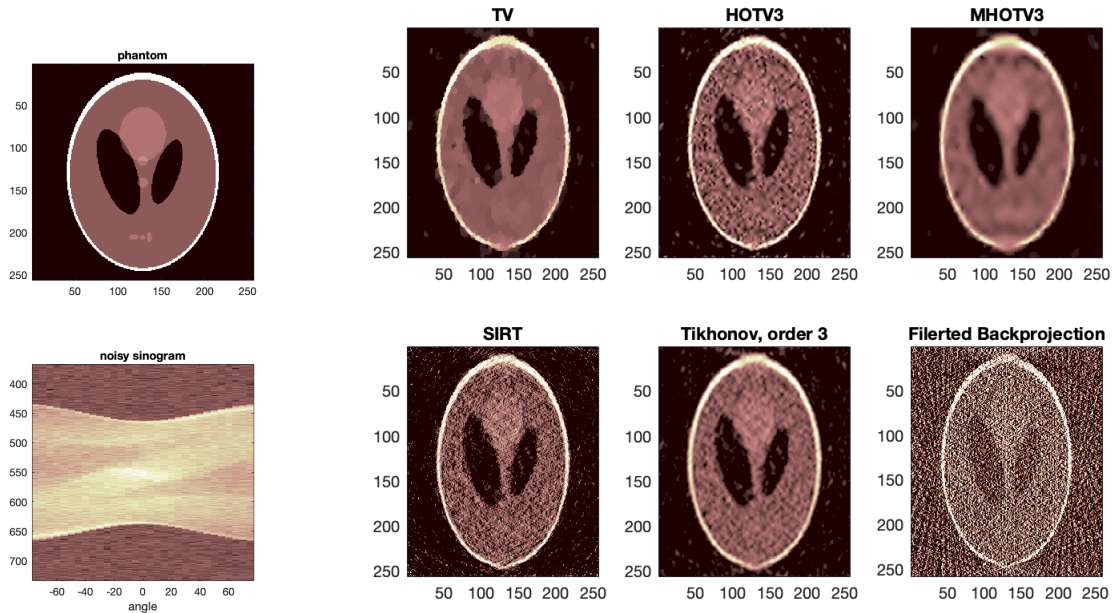


Figure 1: Tomographic reconstruction of phantom image.

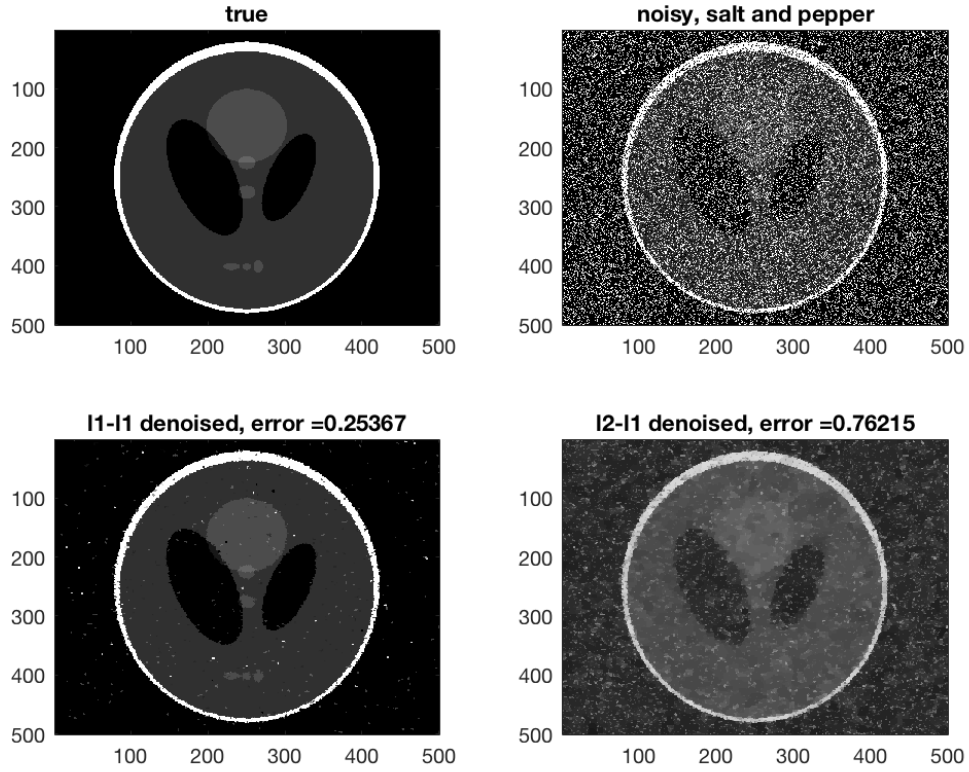


Figure 2: An example of  $\ell_1$  regularization image denoising from salt and pepper noise, comparing the results when the data fitting term is  $\ell_1$  or  $\ell_2$  norm.

## 1.2 HOTV based $\ell_1$ - $\ell_1$ Regularization

- **Code name:** HOTV3D.L1L1
- **Demo:** see demo.L1L1.m
- **Description:** An iterative solver for HOTV  $\ell_1$  regularization minimization for inverse problems, where the data fitting metric is given as the  $\ell_1$  norm. That is given a data vector  $b$ , a map  $A$  that maps the unknown signal  $f$  to  $b$ , the algorithm tries to find

$$\min_f \mu \|Af - b\|_1 + \|D^k f\|_1.$$

All of the options are more or less the same as well HOTV3D. For more details, look in the description given with in the code.

## 1.3 General $\ell_1$ regularization algorithm

- **Code name:** lloptimo
- **Demo:** see demo.MHOTV.m

- **Description:** An iterative solver for general  $\ell_1$  regularization minimization for inverse problems and denoising.

```
% function [U, out] = l1optimo(A,b,n,opts)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%           Problem Description           %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Motivation is to find:

%           min_f { mu/2*||Af - b||_2^2 + ||D f||_1 }

% This algorithm is essentially the same as HOTV3D, however,
% the user must specify the regularization operator "D". To do this,
% the user should input into the opts structure the options opts.D and
% opts.Dt, where opts.D is the regularization transform, and opts.Dt is
% the adjoint of opts.D.
```

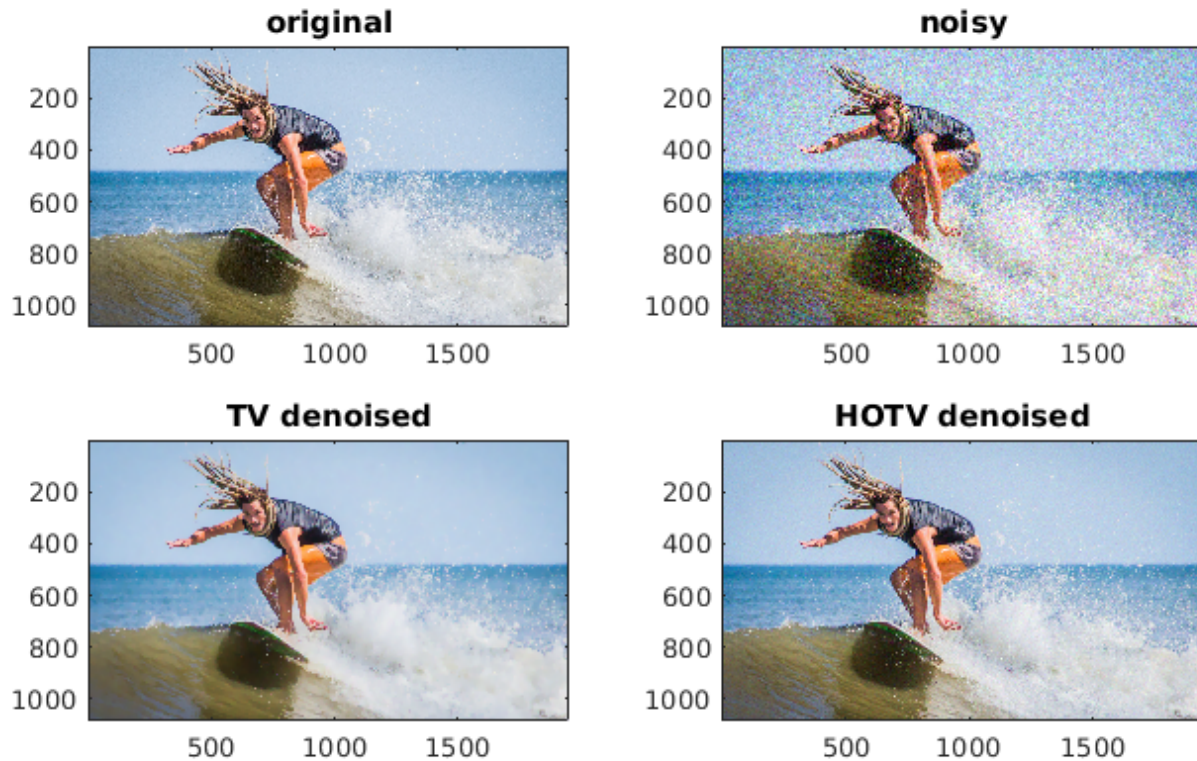


Figure 3: Denoising with  $\ell_1$  regularization.

## 1.4 HOTV $\ell_2$ Tikhonov Regularization

- **Code name:** Tikhonov
- **Demo name:** see demo\_tikhonov.m
- **Description:** An iterative solver for higher order total variation  $\ell_2$  regularization minimization for inverse problems and denoising. That is given a data vector  $b$ , a map  $A$  that maps the unknown signal  $f$  to  $b$ , the algorithm seeks to find

$$\min_f \mu \|Af - b\|_2^2 + \|D^k f\|_2^2.$$

All of the options are more or less the same as well HOTV3D. For more details, look in the description given with in the code.

MATLAB comments:

```
% These functions solve
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% min_x      mu*||Ax-b||^2 + ||Dx||^2
% subject to optional inequality constraints
% D is a finite difference operator
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% options are more or less the same as HOTV3D, see check_hotv_opts or the
% users guide.

% Fields in the opts structure (defaults are assigned for empty fields):
% order - order of the finite difference reg. operator, D
% iter - maximum number of iterations for CG
% mu - regularization parameter (see formulation above)
% tol - convergence tolerance for CG
% levels - default is 1, but for higher integers it uses a multiscale
% operators for D
```

## 1.5 Tomographic reconstruction with SIRT

- **Code name:** SIRT
- **Demo name:** see demo\_tomo.m
- **References:** [7]
- **Description:** Simultaneous iterative reconstruction technique (SIRT) for tomographic reconstruction, which works by the general gradient decent method. MATLAB comments:

```
% function [x,out] = SIRT(stack,angles,recsize,iter,minc,maxc)
%
%DESCRIPTION:
%   %this function performs the SIRT algorithm for tomographic reconstruction.
%
%NOTATION:
```

```

% function [x,out] = SIRT(stack,angles,recsize,iterations,minc,maxc);
%
%INPUTS:
% stack - the tilt series, where it is assumed the tilt axis is horizontal
% and located at the middle of the stack
% angles - a vector holding the projection angles of the stack, in order,
% in degrees
% recsize - the dimension of the reconstruction
% iter - the number of SIRT iterations
% minc - minimum density constraint, e.g. U>=0.
% maxc - maximum density constraint, e.g. U<=1.
%
% default values are used for recsize, iter, and minc if they are not
% specified, therefore one may simply input "sirtten(stack,angles)."
% the recsize will be set to the detector count, i.e. size(stack,1)
% 50 iterations is default, and no density constraint is used if it is not
% specified
%
%OUTPUT:
% x - the reconstruction from the input tilt series and other input
% parameters
% out - additional outputs

```

- **Additional Notes:** For automated reconstruction of a 3D volume see the algorithm *sirtauto.m*.

## 1.6 Discrete tomographic reconstruction with DART

I have removed the description of this code, though it is still included in the package. Please see previous versions or email me directly for information.

## 2 Image Alignment

### 2.1 Basic Cross Correlation

- **Code names:** `cross_corr.m` and `cross_corr_pad.m`
- **Demo name:** see `demo_align.m`
- **Description:** these algorithms perform 2D image alignment from an input 3D stack of images by cross correlation. “`cross_corr.m`” maintains the original image size by simply rotating or circular shifting the image and “`cross_corr_pad.m`” pads the stack with zeros based on the minimum and maximum shifts. MATLAB comments:

```

%DESCRIPTION
%This function performs cross correlation of an input stack of images.
%
%NOTATION
%[stacknew,shifts]=cross_corr(stack,startslice);
%

```

```

%INPUTS
    %stack - 3D matrix assumed to be a stack of images to be cross
        %correlated
    %startslice - the reference image that all slices are consecutively
    %aligned to. This image will not move
    %
%OUTPUTS
    %stack- 3D stack of images after cross correlation
    %shifts - shifts that were applied to each image
    %
%NOTE: This function automatically uses a window to improve alignment. To
    %remove the windowing, set pwr=0.

```

## 2.2 Center of mass alignment for tilt series alignment

- **Code names:** COM\_align.m
- **Demo name:** see demo\_align.m
- **References:** [6]
- **Description:** Center of mass alignment for electron tomography data. See <http://ascimaging.springeropen.com/articles/10.1186/s40679-015-0005-7> for details. MATLAB comments:

```

% Center of mass alignment for electron tomography data
%
% function [stack,shifts,usables] = COM_align(stack,angles,ratio,s)
%
% Inputs: stack is 3-D matrix containing tomography data
% angles are the angles in degrees
% ratio is the ratio of slices to be used for each projection
% s is the number of projections used as a sequence to determine rigid
% alignment. Setting s to be the number of angles is equivalent to the
% alignment method published here:
% http://ascimaging.springeropen.com/articles/10.1186/s40679-015-0005-7
%
%
% The ratio variable:
% should be input as a number between 0 and 1, where the user rates the
% consistency of the stacks through the slices. From our experience, very
% small values of s are better. If the user does not input a
% rating, the default value of .1 is used. Setting ratio
% to perfect 1 would mean that through the slices, there is significant amount
% of mass in all of the slices, and very little mass moves in or out as the
% tilt angle changes. A lower ratio would mean otherwise.
% This rating is then used to determine how many slices to use for the
% center of mass alignment. For example, if you set the rating to .2, then

```



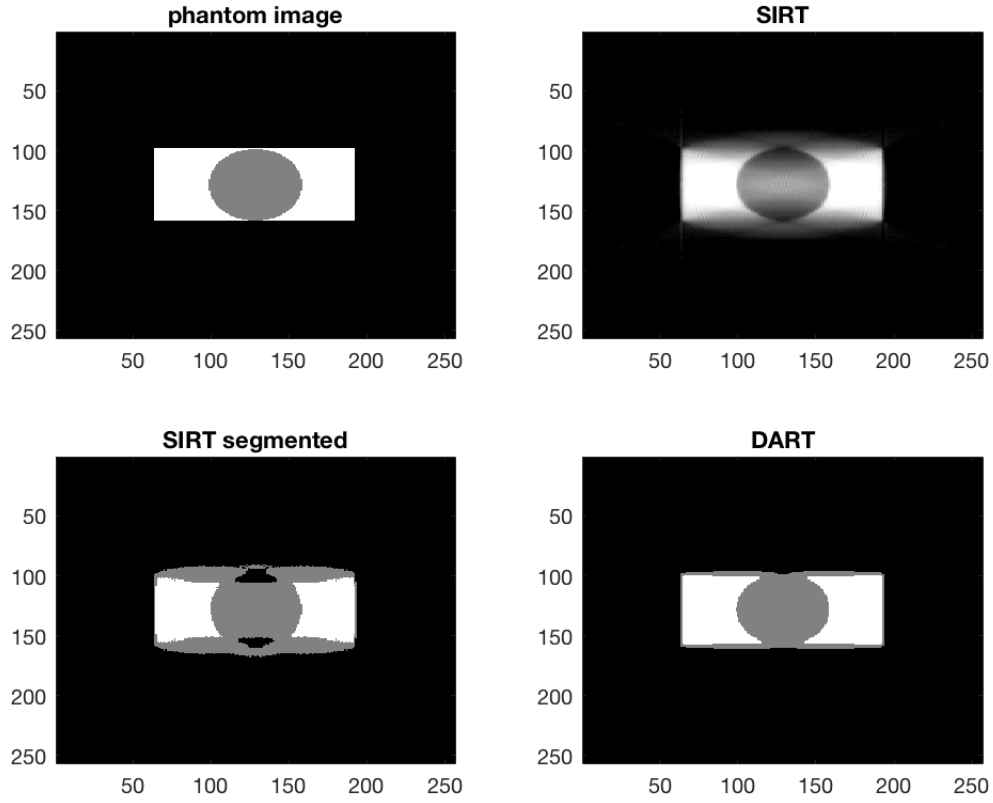


Figure 4: Tomographic reconstruction with DART.

```
% only the best 20 percent of the slices will be used in the alignment step.
% That way, if the the stack has some slices with very little mass, yet
% mass moves into these slices at high angles, these slices may be ignored
% for the alignment.
```

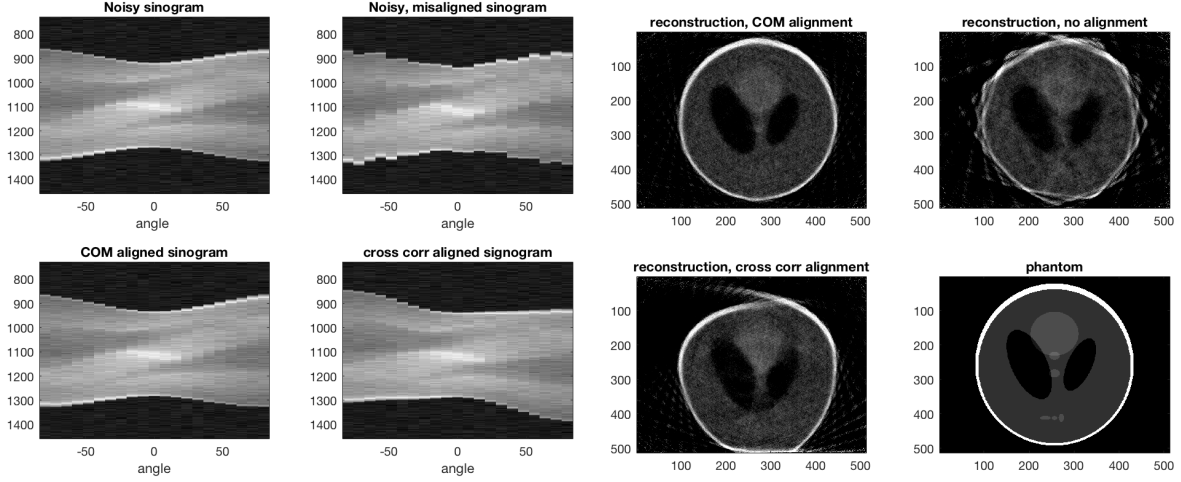


Figure 5: Tomographic alignment and reconstruction (SIRT).

### 3 Other utilities and codes potentially of interest

\*See the comments within each code for details.

- `add_Wnoise.m` - add Gaussian white noise to data with specified SNR.
- `Tikhonov.m` - a solver for inverse problems that uses Tikhonov regularization. It is similar to `HOTV3D`, except the regularization uses the  $\ell_2$  norm.
- `moviestack.m` - used to visualize a 3D volume by passing through 2D cross-sections.
- `radonmatrix.m` - builds a sparse projection matrix for tomography based off of input geometry.
- `corr_x_global.m` - a horizontal image alignment procedure for a tilt series based off of the conservation of mass.
- `manualalign.m` - a utility that can be used to manually align images.
- `forward_proj.m` - builds a tilt series given input projection angles and 3D volume.

### References

- [1] Tony Chan, Antonio Marquina, and Pep Mulet. High-order total variation-based image restoration. *SIAM J. Sci. Comput.*, 22(2):503–516, 2000.
- [2] Chengbo Li. *An efficient algorithm for total variation regularization with applications to the single pixel camera and compressive sensing*. PhD thesis, Rice University, 2009.
- [3] Chengbo Li, Wotao Yin, Hong Jiang, and Yin Zhang. An efficient augmented lagrangian method with applications to total variation minimization. *Comput. Optim. Appl.*, 56(3):507–530, 2013.
- [4] Toby Sanders, Anne Gelb, Rodrigo B Platte, Ilke Arslan, and Kai Landskron. Recovering fine details from under-resolved electron tomography data using higher order total variation  $\ell_1$  regularization. *Ultramicroscopy*, 174:97–105, 2017.

- [5] Toby Sanders and Rodrigo B Platte. Multiscale higher-order tv operators for l1 regularization. *Advanced structural and chemical imaging*, 4(1):12, 2018.
- [6] Toby Sanders, Micah Prange, Cem Akatay, and Peter Binev. Physically motivated global alignment method for electron tomography. *Advanced Structural and Chemical Imaging*, 1(1):1–11, 2015.
- [7] Jeannot Trampert and Jean-Jacques Leveque. Simultaneous iterative reconstruction technique: Physical interpretation based on the generalized least squares solution. *J. Geophys. Res.*, 95(12):553–9, 1990.