

User Guide for `deconvtv` (MATLAB Version 1.0)

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September 23, 2013

1 Introduction

`deconvtv` is a numerical algorithm for solving total variation constrained least-squares problems. The concept of the algorithm is based on an augmented Lagrangian method proposed in [1], and is a variation of the popularly known Alternating Direction Methods of Multipliers (ADMM) [2, 3]. In particular, `deconvtv` solves the following minimization problems

$$\underset{\mathbf{f}}{\text{minimize}} \quad \frac{\mu}{2} \|\mathbf{H}\mathbf{f} - \mathbf{g}\|_2^2 + \|\mathbf{f}\|_{TV}, \quad (1)$$

$$\underset{\mathbf{f}}{\text{minimize}} \quad \mu \|\mathbf{H}\mathbf{f} - \mathbf{g}\|_1 + \|\mathbf{f}\|_{TV}, \quad (2)$$

where \mathbf{H} is a circulant matrix denoting a spatially invariant linear operator, μ is a regularization parameter, and $\|\mathbf{f}\|_{TV}$ is the total variation norm of the data \mathbf{f} , defined as

$$\|\mathbf{f}\|_{TV} = \sum_k \sqrt{\beta_x [\mathbf{D}_x \mathbf{f}]_k^2 + \beta_y [\mathbf{D}_y \mathbf{f}]_k^2 + \beta_t [\mathbf{D}_t \mathbf{f}]_k^2}.$$

Here, $[\mathbf{f}]_k$ is the k -th entry of the vector \mathbf{f} . The operators \mathbf{D}_x , \mathbf{D}_y and \mathbf{D}_t are the gradient operators along the horizontal, vertical and temporal directions. The relative emphasis of \mathbf{D}_x , \mathbf{D}_y and \mathbf{D}_t can be controlled by β_x , β_y and β_t , respectively.

2 User Interface

The user interface of `deconvtv` is as follows:

```
out = deconvtv(g, h, mu, opts);
```

2.1 Input Variables

- **g**: Input image. It can be a gray-scaled image, color image, or gray-scaled video.
- **h**: Point spread function, could be a two-dimensional matrix, or a three-dimensional tensor.
- **mu**: Regularization parameter μ .
- **opts**: A structure of options (See below).

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2.2 Option Fields

All default settings are marked in `{.}`.

- `opts.method`: Defines the method to be used, either `'11'` or `{'12'}`. If `'12'` is chosen, then `deconvtv` solves Problem (1). If `'11'` is chosen, then `deconvtv` solves Problem (2).
- `opts.beta`: An 1×3 vector specifying $(\beta_x, \beta_y, \beta_t)$. Default is `{[1, 1, 0]}`. For video deblurring and denoising, `opts.beta` can be chosen as `[1, 1, 2.5]`.
- `opts.rho_r`: Regularization parameter to the constraint violation $\|\mathbf{u} - \mathbf{Df}\|^2$ (See [1]). Default is `{2}`.
- `opts.rho_o`: Regularization parameter to the constraint violation $\|\mathbf{Hf} - \mathbf{g} - \mathbf{r}\|^2$ (See [1]). Default is `{50}`.
- `opts.alpha`: Criteria for `rho_r` update (See [1]). Default is `{0.7}`.
- `opts.gamma`: Update constant for `rho_r` (See [1]). Default is `{2}`.
- `opts.max_itr`: Maximum number of iteration `{20}`.
- `opts.tol`: Tolerance level of relative change. Default is `{1e-3}`.
- `opts.print`: Print intermediate report, either `'true'` or `'false'`. Default is `{false}`.
- `opts.f`: Initial guess. Default is `{g}`.
- `opts.y1`, `opts.y2`, `opts.y3`: Initial guess of Lagrange multipliers for the constraint $\mathbf{u} = \mathbf{Df}$. Default is `{0}`.
- `opts.z`: Initial guess of Lagrange multiplier for the constraint $\mathbf{r} = \mathbf{Hf} - \mathbf{g}$. Default is `{0}`.

2.3 Output Variables

- `out.f`: Output image, or video.
- `out_itr`: total number of iterations elapsed
- `out.relchg`: final relative change
- `out.Df1`, `out.Df2`, `out.Df3`: Output image gradients
- `out.y1`, `out.y2`, `out.y3`: Output Lagrange multipliers
- `out.rho_r`: final regularization parameter

3 Examples

3.1 Image Denoising

Image Denoising Example

```
% Prepare images
f_orig = im2double(imread('./data/wind.jpg'));
[rows cols frames] = size(f_orig);
H      = fspecial('gaussian', [9 9], 2);
g      = imfilter(f_orig, H, 'circular');
g      = imnoise(g, 'salt & pepper', 0.05);

% Setup parameters (for example)
opts.rho_r = 5;          opts.rho_o = 100;          opts.beta = [1 1 0];
opts.print = true;      opts.alpha = 0.7;          opts.method = 'l1';

% Setup mu
mu = 20;

% Main routine
tic
out = deconvtv(g, H, mu, opts);
toc

% Display results
figure(1); imshow(g);      title('input');
figure(2); imshow(out.f);  title('recovered');
```



(a) Input Image



(b) Recovered Image

Figure 1: Example: Image denoising. Time elapsed: 2.2 seconds.

3.2 Image Deblurring

Image Deblurring Example

```
% Prepare images
f_orig = im2double(imread('./data/building.jpg'));
[rows cols frames] = size(f_orig);
H      = fspecial('gaussian', [9 9], 2);
g      = imfilter(f_orig, H, 'circular');
g      = imnoise(g, 'gaussian', 0, 0.00001);

% Setup parameters (for example)
opts.rho_r = 2;      opts.beta = [1 1 0];      opts.print = true;
opts.alpha = 0.7;   opts.method = 'l2';

% Setup mu
mu = 10000;

% Main routine
tic
out = deconvtv(g, H, mu, opts);
toc

% Display results
figure(1); imshow(g);      title('input');
figure(2); imshow(out.f);  title('recovered');
```



(a) Input Image



(b) Recovered Image

Figure 2: Example: Image deblurring. Time elapsed: 8.24 seconds.

3.3 Video Disparity Refinement

Video Disparity Refinement Example

```
folder_name = './data/';

fname = sprintf('%sdata%04d.jpg', folder_name, 1);
f = im2double(imread(fname));
[rows cols frames] = size(f);
g = zeros(rows,cols,frames);

for fidx = 1:10
    fname = sprintf('%sdata%04d.jpg', folder_name, fidx);
    f = im2double(imread(fname));
    if size(f,3)>1
        g(:,:,fidx) = rgb2gray(f);
    else
        g(:,:,fidx) = f;
    end
end

% Setup parameters (for example)
opts.beta = [1 1 10];    opts.print = true;    opts.method = 'l1';

% Setup mu
mu = 1;

% Main routine
tic
out = deconvtv(g, 1, mu, opts);
toc

% Display results
figure(1); imshow(g(:,:,5));    title('input');
figure(2); imshow(out.f(:,:,5)); title('recovered');
```



Figure 3: Example: Video disparity refinement. Top: Input. Bottom: Recovered. Time elapsed: 12.1 seconds for 10 frames.

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References

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