## MATH473 HW2

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## 1 Problem 1

$$f(x) = -|x| \Rightarrow f(x) = \begin{cases} x & x < 0 \\ -x & x \ge 0 \end{cases}$$

$$f'(0_+) = \lim_{h \to 0} \frac{f(0+h) - f(0)}{h} = \frac{-h - 0}{h} = -1$$

$$f'(0_-) = \lim_{h \to 0} \frac{f(0) - f(0-h)}{h} = \frac{0 - (-h)}{h} = 1$$

$$\Rightarrow f'(0_+) \ne f'(0_-)$$

So f(x) is not differentiable at 0.

Define v(x) as the weak derivative of f, then we have:

$$\int_{-\infty}^{\infty} f \phi' dx = -\int_{-\infty}^{\infty} \phi v dx \quad \text{for any} \quad \phi(x) \in C_0^{\infty}(-\infty, +\infty)$$

$$\int_{-\infty}^{\infty} f \phi' dx = \int_{-\infty}^{0} x \phi' dx - \int_{0}^{\infty} x \phi' dx$$
$$= \int_{-\infty}^{0} x d\phi - \int_{0}^{\infty} x d\phi$$
$$= x \phi(x) \Big|_{-\infty}^{0} - \int_{-\infty}^{0} \phi(x) dx - x \phi(x) \Big|_{0}^{\infty} + \int_{0}^{\infty} \phi(x) dx$$

Becasue 
$$\phi(\infty) = \phi(-\infty) = 0$$
  

$$= \int_0^\infty \phi(x)dx - \int_{-\infty}^0 \phi(x)dx$$
 (1)  

$$= -\int_{-\infty}^\infty v(x)dx$$
 (2)

By comparing equations (1) and (2), we can find a weak derivative of f:

$$v(x) = \begin{cases} 1 & x < 0 \\ 0 & x = 0 \\ -1 & x > 0 \end{cases}$$

## 2 Problem 2

The paper proposes to denoise images by minimizing the total variation norm of the estimated solution. A constrained minimization algorithm is derived as a time dependent nonlinear PDE, where the constraints are determined by the noise statistics.

First let  $u_0(x, y)$  denote the pixel values of a noisy image. Let u(x, y) denote the desired clean image and n(x, y) denote the additive noise.

$$u_0(x,y) = u(x,y) + n(x,y) \qquad x, y \in \Omega$$
(1)

The paper uses total variation (TV) norm ( $L_1$  norms) to estimate the image. Although  $L_1$  estimation is nonlinear and computationally complex, it has been conjectured that  $L_1$  norm is more appropriate than  $L_2$  norm for image estimation. In fact  $L_1$  norm is good for shock calculation by removing spurious oscillations and preserve sharp signals. And it's the space of functions of bounded total variation BV. The derived constrained minimization problem is:

$$minimize \int_{\Omega} \sqrt{u_x^2 + u_u^2} dx dy \tag{2}$$

The two constraints make sure the mean and standard deviation of the noise n(x, y) are respectively 0 and  $\sigma$ :

$$\int_{\Omega} u \mathrm{d}x \mathrm{d}y = \int_{\Omega} u_0 \mathrm{d}x \mathrm{d}y \tag{3}$$

$$\int_{\Omega} \frac{1}{2} (u - u_0)^2 dx dy = \sigma^2 \quad , \text{ where} \quad \sigma > 0 \quad \text{is given.}$$
 (4)

The solution procedure of equations (2-4) is based on Euler-Lagrange equations, which converts the optimization problem to a PDE problem (5-6). The PDE is time dependent and as time increases, the image will approach its denoised version.  $\lambda$  can develop with time or be a constant.

$$u_t = \frac{\partial}{\partial x} \left( \frac{u_x}{\sqrt{u_x^2 + u_y^2}} \right) + \frac{\partial}{\partial y} \left( \frac{u_y}{\sqrt{u_x^2 + u_y^2}} \right) - \lambda (u - u_0) \qquad t > 0, \quad x, y \in \Omega$$
 (5)

$$u(x, y, 0)$$
 is given and  $\frac{\partial u}{\partial n} = 0$  on  $\Omega$  (6)

A numerical method is used for (5-6) and the algorithm is tested on graphs and real images. The concludes include that TV denoising is better than a Weiner filter denoising. The discontinuities are much clearer in TV denoising while Weiner filter denoising has oscillatory artifacts.

# 3 Problem 3

## 3.1

To compare TV and Tikhonov inpainting, I set the same parameters: the ratio of missing pixels is 0.7, the time step is  $10^{-7}$  and the tolerance is  $10^{-5}$ . Their PSNR and relative errors are shown below the Figure 1 and 2. Although their PSNR and relative errors are close, the result of TV inpainting looks better with sharper edges.





Figure 1: Tikhonov inpainting: PSNR=24.6106, relative error=0.1131.





Figure 2: TV inpainting.: PSNR=24.2277, relative error=0.1181

#### 3.2

When the ratio of missing pixels increases, the image  $u_0$  with missing intensities will be less informative. Therefore, with a higher ratio of missing pixels, the quality of inpainting will be worse with smaller PSNR and larger relative errors.

Figure 3 and 4 shows Tikhonov inpainting with 0.8 and 0.9 missing intensities. Figure 5 and 6 shows TV inpainting with 0.8 and 0.9 missing intensities.





Figure 3: Tikhonov inpainting: 0.8 missing intensities, PSNR=23.1858, relative error=0.1332.

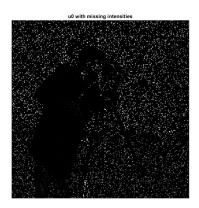




Figure 4: Tikhnov inpainting.: 0.9 missing intensities, PSNR=21.4394, relative error=0.1629





Figure 5: TV inpainting: 0.8 missing intensities, PSNR=22.5524, relative error=0.1433.





Figure 6: TV inpainting.: 0.9 missing intensities, PSNR=20.3209, relative error=0.1853

## 3.3

Implementing Tikhonov and TV denoising with  $\lambda = 10^d$ , Table 1 and 2 show PSNR and relative errors with different  $\lambda$  by changing values of d.

$\lambda = 10^d$	PSNR	Relative error
d=4	20.1052	0.1899
d=4.5	22.0334	0.1521
d=5	23.9936	0.1214
d=5.5	24.5808	0.1134
d=6	22.9051	0.1376
d=6.5	21.2215	0.1671

Table 1: Tikhonov denoising

$\lambda = 10^d$	PSNR	Relative error
d=2.5	20.2099	0.1877
d=3	22.9329	0.1372
d=3.5	26.6046	0.0899
d=4	24.3952	0.1159
d=4.5	21.4515	0.1627
d=5	20.4667	0.1822

Table 2: TV denoising

Obviously, when d = 5.5, the result of Tikhonov denoising has the largest PSNR. And when d = 3.5, the result of TV denoising has the largest PSNR. Show these two results in Figure 7 and 8.





Figure 7: Tikhonov denoising: d=5.5





Figure 8: TV denoising: d=3.5

## 3.4

Using the TV inpainting algorithm in 3.1 to remove the texts, the result is shown below in Figure 9.





Figure 9: Removing texts with TV denoising

#### 4 Matlab Code

## 4.1 Tikhonov inpainting

```
1 function [u] = Tik_inpainting(u0, mask, e, dt)
      TIK_INPAINTING by Jiasen Zhang
4 % input
5 % u0 = image with missing intensities
\varepsilon % mask = 1 as location of missing intensities
  % e = tolerance
8 % dt = tiem step
10 % output
11 % u = result
13 [m, n] = size(u0);
14 h = 1/\min(n, m); % here m=n
  u=u0;
16 lu = zeros(m,n); % size Laplace u
  for k=1:200000 % set a max iteration
17
       % Laplace u
18
       lu(2:m-1,2:n-1) = u(3:m,2:n-1) + u(1:m-2,2:n-1) + ...
19
20
           u(2:m-1,3:n) + u(2:m-1,1:n-2) - 4 + u(2:m-1,2:n-1);
       unew=u+2*dt*lu/(h^2);
21
       % boundary condition
       unew(1,:) = unew(2,:);
23
       unew (m, :) = unew (m-1, :);
24
       unew(:,1) = unew(:,2);
25
       unew(:, n) = unew(:, n-1);
26
27
       % u=u0 on D
       unew (mask\neq1) =u0 (mask\neq1);
28
       d=max(max(abs(u-unew))); % difference
29
30
       if mod(k, 200) == 0
            fprintf('%3e, %d\n',d,k);
31
32
       end
       u=unew;
33
34
       if d<e
           break
35
       end
36
37 end
38
39 figure();
40 subplot (1,2,1);
41 imagesc(u0);
axis square;colormap(gray);set(gca,'XTickLabel','','YTickLabel','');
43 title('u0 with missing intensities');
44 subplot (1,2,2);
45 imagesc(u);
46 axis square; colormap(gray); set(gca, 'XTickLabel', '', 'YTickLabel', '');
47 title('Tikhonov inpainting');
48
49
  end
```

### 4.2 TV inpainting

```
1 function [u] = TV_inpainting(u0, mask, e, dt)
2 % TV_INPAINTING by Jiasen Zhang
3
```

```
4 % input
5 % u0 = image with missing intensities
6 % mask = 1 as location of missing intensities
  % e = tolerance
   % dt = time step
10 % output
11 % u = result
13 [m, n] = size(u0);
14 h = 1/\min(n, m); % here m=n
15 du = zeros(m,n);
16 divuy = du;
17 divux = du;
18 11=110:
19 tau = 1e-6; % small term in the denominator
  for k=1:200000 % set a max iteration
20
21
       % given u
22
       % get divux and divuy
       duxf = u(3:m,2:n-1)-u(2:m-1,2:n-1); % forward difference of x direction
23
       duxb = u(2:m-1,2:n-1)-u(1:m-2,2:n-1); % backward difference of x direction
24
       \label{eq:duyf} \texttt{duyf} = \texttt{u(2:m-1,3:n)-u(2:m-1,2:n-1);} \ \text{\% forward difference of y direction}
25
       duyb = u(2:m-1,2:n-1)-u(2:m-1,1:n-2); % backward difference of y direction
26
       divux(2:m-1,2:n-1) = duxf./(sqrt(tau*ones(m-2,n-2)+duxf.^2...
27
            +minmod(duyf,duyb).^2));
28
       divuy(2:m-1,2:n-1) = duyf./(sqrt(tau*ones(m-2,n-2)+duyf.^2...
           +minmod(duxf,duxb).^2 ));
        % get du
29
       du(2:m-1,2:n-1) = divux(2:m-1,2:n-1)-divux(1:m-2,2:n-1)...
30
           + divuy(2:m-1,2:n-1)-divuy(2:m-1,1:n-2);
31
32
       % unew
       unew=u+dt*du/h;
33
       % boundary condition
       unew(1,:) = unew(2,:);
35
       unew (m, :) = unew (m-1, :);
36
37
       unew(:,1) = unew(:,2);
       unew(:, n) = unew(:, n-1);
38
39
       % u=u0 on D
       unew (mask\neq1) =u0 (mask\neq1);
40
       d=max(max(abs(u-unew))); % difference
41
42
         if mod(k, 200) == 0
              fprintf('%3e, %d\n',d,k);
43
44
         end
       u=unew:
45
       if d<e
47
           break
48
       end
49 end
50
51 figure();
52 subplot (1,2,1);
53 imagesc(u0);
axis square;colormap(gray);set(gca,'XTickLabel','','YTickLabel','');
55 title('u0 with missing intensities');
56 subplot (1,2,2);
57 imagesc(u);
  axis square;colormap(gray);set(gca,'XTickLabel','','YTickLabel','');
58
59 title('TV inpainting');
60
61 % minmod
62 function result = minmod(a,b)
63 % minmod(a,b)
result=(sign(a) + sign(b)) . *min(abs(a), abs(b))/2;
65 end
66 end
```

## 4.3 Tikhonov denoising

```
1 function [u] = Tik_denoising(J, scratch, e, dt, lambda)
      TIK_DENOISING by Jiasen Zhang
4 % input
5 % J = image with missing intensities
6 % scratch = 0 as location of missing intensities
  % e = tolerance
8 % dt = tiem step
9 % lambda = a parameter
11 % output
  % u = result
12
13
14 [m, n] = size(J);
15 h = 1/\min(n,m); % here m=n
16 u=J;
   lu = zeros(m,n); % size Laplace u
   for k=1:200000 % set a max iteration
18
19
       % Laplace u
       lu(2:m-1,2:n-1) = u(3:m,2:n-1) + u(1:m-2,2:n-1) + ...
20
          u(2:m-1,3:n) + u(2:m-1,1:n-2) - 4 + u(2:m-1,2:n-1);
21
22
       uD = u;
       uD(scratch==0)=0;
23
       JD = J;
25
       JD(scratch==0)=0;
       unew=u + 2*dt*lu/(h^2) - dt*lambda*(uD-JD);
26
27
       % boundary condition
28
       unew(1,:) = unew(2,:);
       unew (m, :) = unew (m-1, :);
30
       unew(:,1) = unew(:,2);
31
       unew(:, n) = unew(:, n-1);
32
       d=max(max(abs(u-unew))); % difference
33
       %d = norm(u-unew)/norm(u);
       if mod(k, 200) == 0
35
           fprintf('%e, %d\n',d,k);
36
       end
37
       u=unew;
38
       if d<e
           break
40
41
42 end
43 figure();
44 subplot (1,2,1);
45 imagesc(J);
  axis square;colormap(gray);set(gca,'XTickLabel','','YTickLabel','');
47 title('u0 with noise');
48 subplot(1,2,2);
49 imagesc(u);
50 axis square;colormap(gray);set(gca,'XTickLabel','','YTickLabel','');
51 title('Tikhonov denoising');
52
53 end
```

#### 4.4 TV denoising

```
1 function [u] = TV_denoising(J, scratch, e, dt, lambda)
2 % TV_DENOISING by Jiasen Zhang
```

```
3
4 % input
5 % J = image with missing intensities
6 % scratch = 0 as location of missing intensities
7 % e = tolerance
8 % dt = tiem step
9 % lambda = a parameter
10
11 % output
12 % u = result
13
[m,n]=size(J);
   h = 1/\min(n,m); % here m=n
15
16 % size of matrices
17 11=zeros(m.n):
18 divux=u; divuy=u;
19 du = u;
20
   tau = 1e-8; % small term in the denominator
21
   for k=1:200000 % set a max iteration
22
        % given u
        % get divux and divuy
24
        duxf = u(3:m,2:n-1)-u(2:m-1,2:n-1); % forward difference of x direction
25
        \texttt{duxb} \; = \; \texttt{u} \, (2 \colon \texttt{m-1}, 2 \colon \texttt{n-1}) \, - \, \texttt{u} \, (1 \colon \texttt{m-2}, 2 \colon \texttt{n-1}) \, ; \; \; \$ \; \; \texttt{backward} \; \; \texttt{difference} \; \; \texttt{of} \; \; \texttt{x} \; \; \texttt{direction}
26
        duyf = u(2:m-1,3:n)-u(2:m-1,2:n-1); % forward difference of y direction
27
28
        duyb = u(2:m-1,2:n-1)-u(2:m-1,1:n-2); % backward difference of y direction
        divux(2:m-1,2:n-1) = duxf./(sqrt(tau*ones(m-2,n-2)+duxf.^2...
29
             +minmod(duyf,duyb).^2));
        \label{eq:divuy} \texttt{divuy}(2:m-1,2:n-1) = \texttt{duyf./(sqrt(tau*ones(m-2,n-2)+duyf.^2 ...})}
30
             +minmod(duxf, duxb).^2));
31
        % get du
        du(2:m-1,2:n-1) = divux(2:m-1,2:n-1)-divux(1:m-2,2:n-1)...
32
             + divuy(2:m-1,2:n-1)-divuy(2:m-1,1:n-2);
        uD = u:
34
        uD(scratch==0)=0;
35
36
        JD = J;
        JD(scratch==0)=0;
37
38
         % unew
        unew=u + dt*du/h - dt*lambda*(uD-JD);
39
        %unew=u + dt*du/h - dt*lambda*(u-J);
40
41
        % boundary condition
        unew(1,:) = unew(2,:);
42
43
        unew (m, :) = unew (m-1, :);
        unew(:,1) = unew(:,2);
44
        unew(:, n) = unew(:, n-1);
        d=max(max(abs(u-unew))); % difference
46
47
        %d = norm(u-unew)/norm(u);
          if mod(k, 200) == 0
48
               fprintf('%e, %d\n',d,k);
49
          end
50
        u=unew:
51
        if d<e
52
53
             break
        end
54
55 end
56 figure();
   subplot(1,2,1);
   imagesc(J):
59 axis square;colormap(gray);set(gca,'XTickLabel','','YTickLabel','');
60 title('u0 with noise');
61 subplot (1,2,2);
axis square;colormap(gray);set(gca,'XTickLabel','','YTickLabel','');
64 title('TV denoising');
65
```

```
66 function result = minmod(a,b)
67 % minmod(a,b)
68 result=(sign(a)+sign(b)).*min(abs(a),abs(b))/2;
69 end
70 end
```

#### 4.5 Problem 3.1 and 3.2

```
clear all;clc;
2 tic
3 I = imread('cameraman.tif');
4 I = double(I); % change I from unit8 to double precision format
5 % normalize I to intensity [0,1] for easier parameter selection
6 I = (I-min(I(:)))/(max(I(:))-min(I(:)));
7 [m,n] = size(I);
  % amount of removed pixels.
9 perc = 0.7;
10 % random mask, Mask==1 for removed pixels
11 Mask = zeros(m, n);
12 Pick = randperm(m*n); Pick = Pick(1:round(perc*m*n));
13 Mask(Pick) = 1;
14 u0 = I;
15 \quad u0 \, (Mask == 1) = 0;
16 %imagesc(u0);
17
18 e = 1e-5; % tolerance
19 dt = 1e-7;
_{21} % choose one and comment the other one
u = Tik_inpainting(u0, Mask, e, dt); % Tikhonov inpainting
23 %u = TV_inpainting(u0, Mask, e, dt); % TV inpainting
24
25 % compute PSNR
26 mse = sum(sum((u-I).^2))/(m*n);
27 \text{ maxx} = \text{max}(\text{max}(\text{abs}(I)));
28 psnr = 10*log10(maxx*maxx/mse);
29 fprintf('PSNR = %f \n', psnr);
30 % Compute relative error
31 re = norm(u-I, 'fro') / norm(I, 'fro');
32 fprintf('Relative error = %f \n', re);
33 toc
```

### 4.6 Problem 3.3

```
1 clear all;clc;
2 tic
3 I = imread('cameraman.tif');
4 I = double(I); % change I from unit8 to double precision format
5 % normalize I to intensity [0,1] for easier parameter selection
6 I = (I-min(I(:)))/(max(I(:))-min(I(:)));
7 [m,n] = size(I);
8
9 % Zero out intensity of I at scratch to get J
10 load scratch
11 J = I;
12 J(scratch == 0) = 0;
13 % Add noise
14 sigma = 0.1;
```

```
J = J + sigma * randn(size(J));
17 d0 = 3.5;
18 lambda = 10^d0;
19 e = 1e-5; % tolerance
20 	ext{ dt} = 1e-7;
22 % choose one and comment the other one
23 %u = Tik_denoising(J, scratch, e, dt, lambda); % Tik denoising
24  u = TV_denoising(J, scratch, e, dt, lambda); % TV denoising
26
27 % Compute PSNR
28 mse = sum(sum((u-I).^2))/(m*n);
29 \max = \max(\max(abs(I)));
30 psnr = 10*log10(maxx*maxx/mse);
31 fprintf('PSNR = f \ n', psnr);
32 % Compute relative error
33 re = norm(u-I,'fro')/norm(I,'fro');
34 fprintf('Relative error = %f \n', re);
35 toc
```

#### 4.7 Problem 3.4

```
clear all;clc;
2 tic
3 I = imread('cameraman.tif');
4 I = double(I); % change I from unit8 to double precision format
_{5} % normalize I to intensity [0,1] for easier parameter selection
I = (I-min(I(:)))/(max(I(:))-min(I(:)));
  [m,n] = size(I);
9 % Zero out intensities of text
10 load text
11 u0 = I;
12 u0(text == 0) = 0.92;
13 % make sure missing intensities are 1, while other intensities are 2 here
14 text = text + 1;
15
16 % TV inpainting
17 e = 1e-5; % tolerance
18 	 dt = 1e-7;
u = TV_inpainting(u0, text, e, dt); % TV inpainting
20
21 % Compute PSNR
22 mse = sum(sum((u-I).^2))/(m*n);
23 maxx = max(max(I));
psnr = 10*log10(maxx*maxx/mse);
25 fprintf('PSNR = %f \n', psnr);
26 % Compute relative error
27 re = norm(u-I,'fro')/norm(I,'fro');
28 fprintf('Relative error = %f \n', re);
29 toc
```