

MA5710 - Assignment 3

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1. Implementation of EED model.

Code: eed.m

```
1
2 function g = eed(f, scale, k, stepsize, nosteps, verbose, ip)
3 % Edge Enhancing diffusion
4
5 if verbose
6     figure(verbose);
7     subplot(1,2,1);
8     imshow(f);
9     title('Original Image');
10    drawnow;
11 end
12
13 % Diffusion tensor D = D(del_u) = (v1, v2)diag(l1, l2)(v1T, v2T)
14 % D = G^T.diag(c1,c2).G ; G = (gx, gy)
15 g = f;
16 for i = 1:nosteps
17     %Calculating gx, gy and gw at given scale for diffusion tensor;
18     gx = gD( g, scale, 1, 0 ); % Computing the gradient
19     gy = gD( g, scale, 0, 1 );
20
21     grad2 = gx.*gx+gy.*gy;
22     gw = sqrt(grad2);
23
24     %Calculating c1 and c2
25     c2 = exp(-(gw/k).^2);
26     c1 = (1/5)*c2;
27
28     %Calculating diffusion tensor components for tnldStep function
29     a = (c1.*gx.^2 + c2.*gy.^2)./grad2;
30     b = (c2-c1).*gx.*gy./grad2;
31     c = (c1.*gy.^2 + c2.*gx.^2)./grad2;
32
33     g = g + stepsize * tnldStep( g, a, b, c, ip);
34
35     %If verbose show edge enhanced diffusion
36     if verbose
37         figure(verbose);
38         subplot(1,2,2);
39         imshow(g);
40         title('Edge Enhancing Diffusion');
41         drawnow;
42     end
43 end
```

Code: eedtest.m

```
1 % Test eed model
2 clc;
3 clear;
4
5 a=imread('cameraman.tif'); % reading the image
6 a=im2double(a); % normalizing the intensity values to lie between 0 and 1
7
8 ref=a;
9 ad=imnoise(a,'gaussian',0.01); % adding Gaussian noise of mean zero and variance
   0.01
10 timestep=0.2; % timestep size used in numerical approximation
11 Niter=60; % number of iterations
12
13 b = eed(ad,1,0.05,timestep,Niter,1,1); % Edge Enhancing function
14
15 % Arguments
16 % 1 is the noisy image,
17 % 2 is the scale - (variance in Gaussian),
18 % 3 is the lambda value = contrast parameter,
19 % 4 is the timestep size, 5 is the no of iterations,
20 % 6 is the value to show the plot,
21 % 7 is the w value used in numerical approximation
22 % 8 corresponding to choice of the numerical scheme.
```

Output:



Figure 1: Output of eed model for contrast parameter - 0.05

2. Take a standard image(for example, cameraman image), perform Linear diffusion, PMC, EED and compare the respective PSNR values.

Code: **q2.m**

```
1 % Linear diffusion, PMC, EED for cameraman image and their outputs
2 clc;
3 clear;
4
5 a=imread('cameraman.tif'); % reading the image
6 a=im2double(a); % normalizing the instensity values to lie between 0 and 1
7
8 ref=a;
9 ad=imnoise(a,'gaussian',0.01); % adding Gaussian noise of mean zero and variance
    0.01
10 timestep=0.2; % timestep size used in numerical approximation
11 Niter=60; % number of iterations
12
13 alpha=2.7; % Used in Numerical approximation of pmc
14 w= exp(4*alpha/9); % Used in Numerical approximation of pmc
15
16 output_linear = imgaussfilt(ad,1); %Filter the image with Linear Diffusion (
    usingGaussian filter) with sigma = 1
17 output_pmc =pmc(ad,ref,0.5,timestep,Niter,0,w,1); %Filter the image with Perona
    Malik diffusion with lambda = 0.5
18 output_eed = eed(ad,1,0.05,timestep,Niter,0,1); % Filter the image with Edge
    Enhancing Diffusion with lambda = 0.05
19
20 % PSNR - Metric to understand the quality of cleaning
21 psnr_linear = psnr(output_linear,ad); % PSNR value for Linear diffusion with
    sigma = 1
22 psnr_pmc = psnr(output_pmc,ad); % PSNR value for Perona Malik diffusion
    with lambda = 0.5
23 psnr_eed = psnr(output_eed,ad); % PSNR value for Edge Enhancing diffusion
    with lambda = 0.05
24
25 figure(1);
26 montage({ad,output_linear}); % Compare noise and output image of Linear diffusion
27 title('Noisy Image Vs. Linear diffusion (sigma = 1) ');
28
29 figure(2);
30 montage({ad,output_pmc}); % Compare noise and output image of PMC
31 title('Noisy Image Vs. Perona Malik diffusion (lambda = 0.5) ');
32
33 figure(3);
34 montage({ad,output_eed}); % Compare noise and output image of EED
35 title('Noisy Image Vs. Edge Enhancing diffusion (lambda = 0.05) ');
36
37 fprintf('PSNR Value for Linear diffusion with (sigma = 1) = %.2f \n',psnr_linear);
38 fprintf('PSNR Value for PMC with (lambda = 0.5) = %.2f \n',psnr_pmc);
39 fprintf('PSNR Value for EED with (lambda = 0.05) = %.2f \n',psnr_eed);
```

Output:

PSNR Value for Linear diffusion with (sigma = 1) = 20.36

PSNR Value for PMC with (lambda = 0.5) = 21.13

PSNR Value for EED with (lambda = 0.05) = 19.84

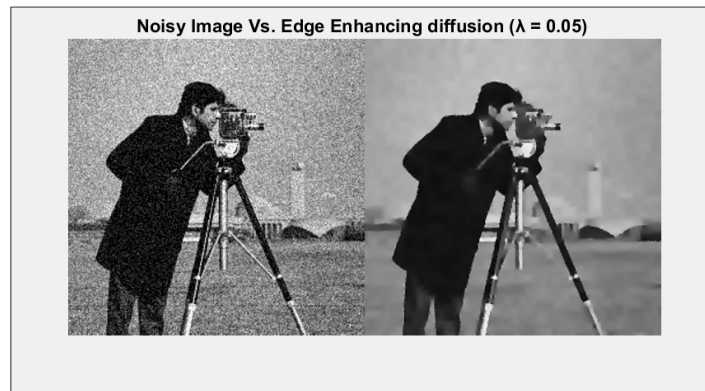
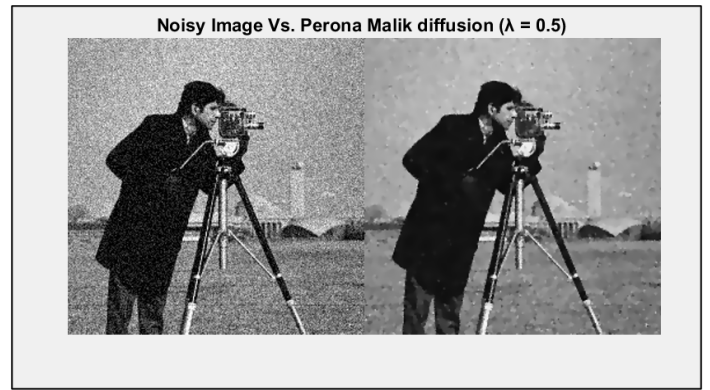
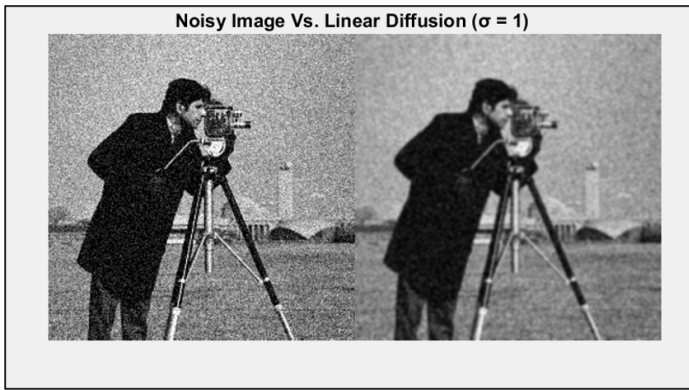


Figure 2: Comparison of all 3 models

3. Take 3 or 4 different images, add different noises to them(Gaussian noise, Salt and Pepper noise, speckle noise and poisson noise with different variances), treat each case as different input image, apply LD, PMC and EED, report respective PSNR values. For better interpretation of your outputs, compare the three models on variance vs PSNR plots for each noise and each image.

Code: q3.m

```
1 % A3-q3
2 clc;
3 clear;
4
5 % Importing 5 images
6 img1 = im2double(imread('cameraman.tif')); % reading the image and normalizing the
       intensity values b/w 0 and 1
7 img2 = im2double(imread('tomo.jpg'));
8 img3 = im2double(im2gray(imread('triangle.jpg'))); % converting color img to
       greyscale
9 img4 = im2double(im2gray(imread('onion.png')));
10 img5 = im2double(imread('eight.tif'));
11
12 n_img = 5; % No. of images
13 n_noise = 10; % No. of noisy images for each image
14
15 % Declare a cellArray of size 5x10 to store noisy images of each image
16 cellArray = cell(n_img,n_noise);
17
18 % Adding Gaussian noise, Poisson, Salt & Pepper noise and speckle noise with
       different variances
19
20 cellArray(1,1) = {img1}; % original image1
21 cellArray(1,2) = {imnoise(img1, 'gaussian',0.01)}; % image with noise
22 cellArray(1,3) = {imnoise(img1, 'gaussian',0.1)};
23 cellArray(1,4) = {imnoise(img1, 'gaussian',0.5)};
24 cellArray(1,5) = {imnoise(img1, 'poisson')};
25 cellArray(1,6) = {imnoise(img1, 'salt & pepper',0.01)};
26 cellArray(1,7) = {imnoise(img1, 'salt & pepper',0.05)};
27 cellArray(1,8) = {imnoise(img1, 'salt & pepper',0.1)};
28 cellArray(1,9) = {imnoise(img1, 'speckle',0.01)};
29 cellArray(1,10) = {imnoise(img1, 'speckle',0.1)};
30
31 cellArray(2,1) = {img2}; % original image2
32 cellArray(2,2) = {imnoise(img2, 'gaussian',0.01)}; % image with noise
33 cellArray(2,3) = {imnoise(img2, 'gaussian',0.1)};
34 cellArray(2,4) = {imnoise(img2, 'gaussian',0.5)};
35 cellArray(2,5) = {imnoise(img2, 'poisson')};
36 cellArray(2,6) = {imnoise(img2, 'salt & pepper',0.01)};
37 cellArray(2,7) = {imnoise(img2, 'salt & pepper',0.05)};
38 cellArray(2,8) = {imnoise(img2, 'salt & pepper',0.1)};
39 cellArray(2,9) = {imnoise(img2, 'speckle',0.01)};
40 cellArray(2,10) = {imnoise(img2, 'speckle',0.1)};
41
42 cellArray(3,1) = {img3}; % original image3
43 cellArray(3,2) = {imnoise(img3, 'gaussian',0.01)}; % image with noise
44 cellArray(3,3) = {imnoise(img3, 'gaussian',0.1)};
45 cellArray(3,4) = {imnoise(img3, 'gaussian',0.5)};
46 cellArray(3,5) = {imnoise(img3, 'poisson')};
47 cellArray(3,6) = {imnoise(img3, 'salt & pepper',0.01)};
```

```

48 cellArray(3,7) = {imnoise(img3, 'salt & pepper',0.05)};
49 cellArray(3,8) = {imnoise(img3, 'salt & pepper',0.1)};
50 cellArray(3,9) = {imnoise(img3, 'speckle',0.01)};
51 cellArray(3,10) = {imnoise(img3, 'speckle',0.1)};
52
53 cellArray(4,1) = {img4}; % original image4
54 cellArray(4,2) = {imnoise(img4, 'gaussian',0.01)}; % image with noise
55 cellArray(4,3) = {imnoise(img4, 'gaussian',0.1)};
56 cellArray(4,4) = {imnoise(img4, 'gaussian',0.5)};
57 cellArray(4,5) = {imnoise(img4, 'poisson')};
58 cellArray(4,6) = {imnoise(img4, 'salt & pepper',0.01)};
59 cellArray(4,7) = {imnoise(img4, 'salt & pepper',0.05)};
60 cellArray(4,8) = {imnoise(img4, 'salt & pepper',0.1)};
61 cellArray(4,9) = {imnoise(img4, 'speckle',0.01)};
62 cellArray(4,10) = {imnoise(img4, 'speckle',0.1)};
63
64 cellArray(5,1) = {img5}; % original image5
65 cellArray(5,2) = {imnoise(img5, 'gaussian',0.01)}; % image with noise
66 cellArray(5,3) = {imnoise(img5, 'gaussian',0.1)};
67 cellArray(5,4) = {imnoise(img5, 'gaussian',0.5)};
68 cellArray(5,5) = {imnoise(img5, 'poisson')};
69 cellArray(5,6) = {imnoise(img5, 'salt & pepper',0.01)};
70 cellArray(5,7) = {imnoise(img5, 'salt & pepper',0.05)};
71 cellArray(5,8) = {imnoise(img5, 'salt & pepper',0.1)};
72 cellArray(5,9) = {imnoise(img5, 'speckle',0.01)};
73 cellArray(5,10) = {imnoise(img5, 'speckle',0.1)};
74
75 % Initialize psnr array to store psnr values
76 psnr_array = zeros(5,10,3);
77
78 % Apply LD, PMC and EED for each noisy images and report respective PSNR values
79
80 timestep = 0.2; % timestep size used in numerical approximation
81 Niter = 60; % number of iterations
82
83 alpha=2.7; % Used in Numerical approximation of pmc
84 w= exp(4*alpha/9); % Used in Numerical approximation of pmc
85
86 for i = 1:n_img
87     for j = 1:n_noise %
88         output_linear = imgaussfilt(cellArray{i,j},0.5); %Filter the image with
            Linear Diffusion ( using Gaussian filter) with sigma = 0.5
89         output_pmc =pmc(cellArray{i,j},cellArray{i,1},0.05,timestep,Niter,0,w,1); %
            Filter the image with Perona Malik diffusion with lambda = 0.05
90         output_eed = eed(cellArray{i,j},1,0.05,timestep,Niter,0,1); % Filter the
            image with Edge Enhancing Diffusion with lambda = 0.05
91         psnr_array(i,j,1) = psnr(output_linear,cellArray{i,1}); % PSNR value
            for Linear diffusion with sigma = 0.5
92         psnr_array(i,j,2) = psnr(output_pmc,cellArray{i,1}); % PSNR
            value for Perona Malik diffusion with lambda = 0.05
93         psnr_array(i,j,3) = psnr(output_eed,cellArray{i,1}); % PSNR value
            for Edge Enhancing diffusion with lambda = 0.05
94
95     end
96 end

```

Output:

PSNR values for each model and image with noise is stored in psnr_array .

Code: q3_PSNRvVar.m

```
1 % A3q3 - PSNR vs variance
2 clc;
3 clear;
4
5 % Importing 5 images
6 img1 = im2double(imread('cameraman.tif')); % reading the image and normalizing the
    intensity values b/w 0 and 1
7 img2 = im2double(imread('tomo.jpg'));
8 img3 = im2double(im2gray(imread('triangle.jpg'))); % converting color img to
    greyscale
9 img4 = im2double(im2gray(imread('onion.png')));
10 img5 = im2double(imread('eight.tif'));
11
12
13 timestep = 0.2; % timestep size used in numerical approximation
14 Niter = 60; % number of iterations
15
16 alpha=2.7; % Used in Numerical approximation of pmc
17 w= exp(4*alpha/9); % Used in Numerical approximation of pmc
18
19 n = 100; % No. of variance values
20 var = logspace(-5,0,n)'; % Variance for the noise
21 ldpsnr = zeros(1,n);
22 pmcpsnr = zeros(1,n);
23 eedpsnr = zeros(1,n);
24 % Apply LD, PMC and EED for each noisy images and report respective PSNR values
25
26 %% Change img and noise for different conditions
27 img = img1; % img = img1, img2, img3, img4, img5
28 noise = "gaussian"; % noise type = gaussian, salt & pepper, speckle
29
30 for i = 1:n
31     output_linear = imgaussfilt(imnoise(img, noise,var(i)),0.5); %Filter the
        image with Linear Diffusion ( using Gaussian filter) with sigma = 0.5
32     ldpsnr(i) = psnr(output_linear,img);
33
34     output_pmc =pmc(imnoise(img, noise,var(i)),img,0.05,timestep,Niter,0,w,1); %
        Filter the image with Perona Malik diffusion with lambda = 0.05
35     pmcpsnr(i) = psnr(output_pmc,img);
36
37     output_eed = eed(imnoise(img, noise,var(i)),1,0.05,timestep,Niter,0,1); %
        Filter the image with Edge Enhancing Diffusion with lambda = 0.05
38     eedpsnr(i) = psnr(output_eed,img);
39 end
40
41 figure(1);
42 plot(var, ldpsnr, 'b-', 'LineWidth', 1);
43 hold on;
44 plot(var, pmcpsnr, 'r-', 'LineWidth', 1);
45 hold on;
46 plot(var, eedpsnr, 'g-', 'LineWidth', 1);
47
48 xlabel('Variance in noise');
49 ylabel('PSNR');
50 title(['Plot of Variance vs PSNR for noise: ', noise]);
51 legend('LD', 'PMC', 'EED');
```

Output:

Given output is for cameraman image and Gaussian noise.

images folder contains output of all combinations of image and noise.

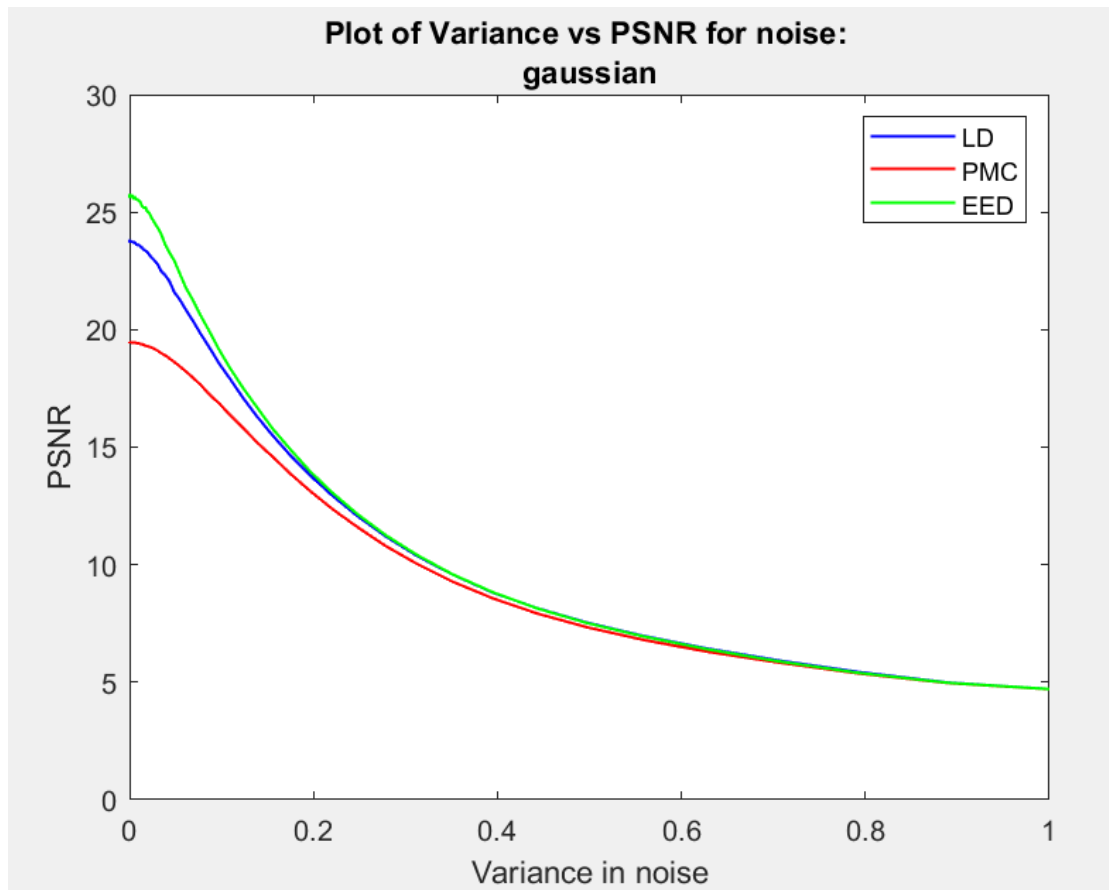


Figure 3: PSNR vs Variance of Gaussian noise for cameraman image

4. Figure out how sensitive are the model parameters? (Hint: For example, You can compare the three models on lambda, contrast parameter vs PSNR plot)

Code: **q4.PSNRvlambda.m**

```
1 % A3q4 - PSNR vs Contrast parameter (lambda)
2 clc;
3 clear;
4
5 % Importing 5 images
6 img1 = im2double(imread('cameraman.tif')); % reading the image and normalizing the
    instensity values b/w 0 and 1
7 img2 = im2double(imread('tomo.jpg'));
8 img3 = im2double(im2gray(imread('triangle.jpg'))); % converting color img to
    greyscale
9 img4 = im2double(im2gray(imread('onion.png')));
10 img5 = im2double(imread('eight.tif'));
11
12
13 timestep = 0.2; % timestep size used in numerical approximation
14 Niter = 60; % number of iterations
15
16 alpha=2.7; % Used in Numerical approximation of pmc
17 w= exp(4*alpha/9); % Used in Numerical approximation of pmc
18
19 n = 100; % No. of variance values
20 lambda = logspace(-5,0,n)'; % Lambda - contasrt parameter
21 ldpsnr = zeros(1,n);
22 pmcpsnr = zeros(1,n);
23 eedpsnr = zeros(1,n);
24 % Apply LD, PMC and EED for each noisy images and report respective PSNR values
25
26 %% Change img and noise for different conditions
27 img = img1; % img = img1, img2, img3, img4, img5
28 noise = "speckle"; % noise type = gaussian, salt & pepper, speckle, poisson
29
30 for i = 1:n
31     output_linear = imgaussfilt(imnoise(img, noise),0.5); %Filter the image with
        Linear Diffusion ( usingGaussian filter) with sigma = 0.5
32     ldpsnr(i) = psnr(output_linear,img);
33
34     output_pmc =pmc(imnoise(img, noise),img,lambda(i),timestep,Niter,0,w,1); %Filter
        the image with Perona Malik diffusion for different lambda
35     pmcpsnr(i) = psnr(output_pmc,img);
36
37     output_eed = eed(imnoise(img, noise),1,lambda(i),timestep,Niter,0,1); % Filter
        the image with Edge Enhancing Diffusion for different lambda
38     pmcpsnr(i) = psnr(output_pmc,img);
39     eedpsnr(i) = psnr(output_eed,img);
40 end
41
42 figure(1);
43 plot(lambda, ldpsnr, 'b-', 'LineWidth', 1);
44 hold on;
45 plot(lambda, pmcpsnr, 'r-', 'LineWidth', 1);
46 hold on;
47 plot(lambda, eedpsnr, 'g-', 'LineWidth', 1);
48 hold off;
```

```

49 xlabel('Contrast parameter, Lambda');
50 ylabel('PSNR');
51 title(['Plot of Lambda vs PSNR for noise: ', noise]);
52 legend('LD', 'PMC', 'EED');

```

Output:

Output images of different combinations of image and noise is in **images** folder.

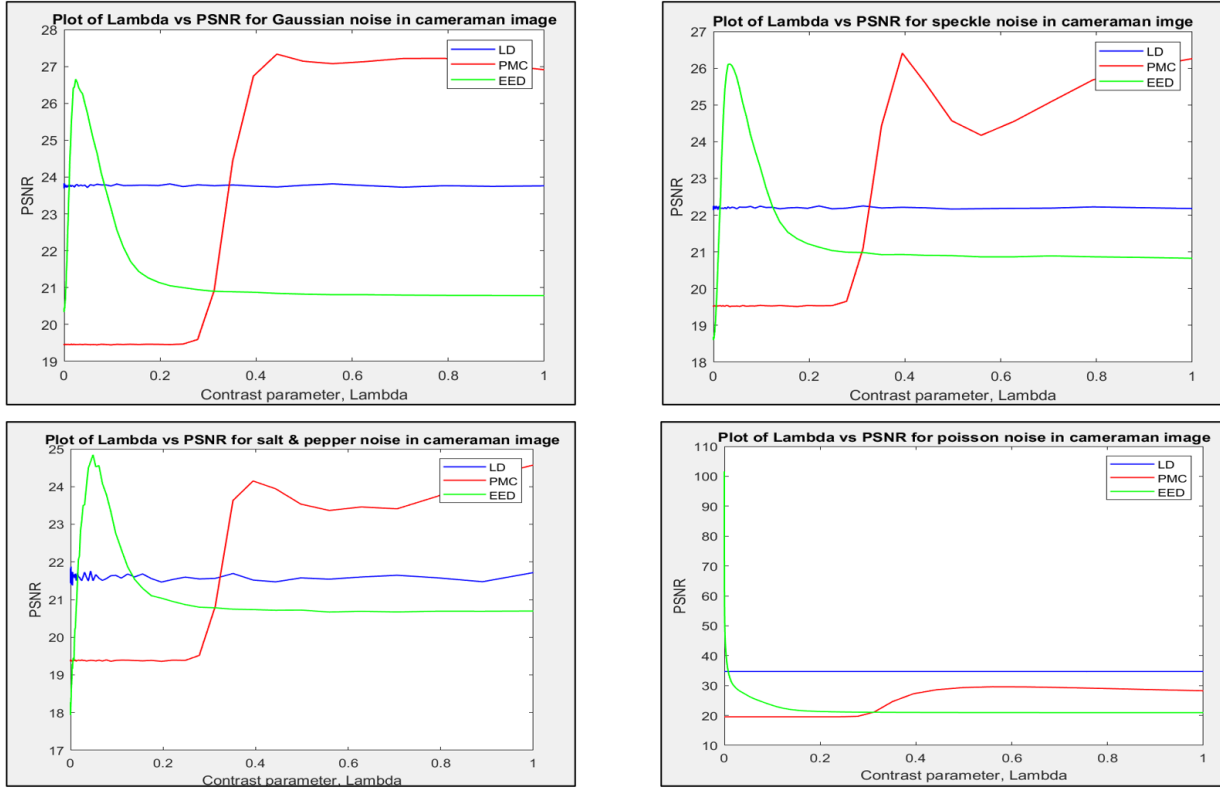


Figure 4: PSNR vs Lambda for cameraman image with different noises

Code: eedtest_sigmaVlambda.m

```
1 %% EED Model- contrast parameter lambda & smoothing parameter sigma relation
2 clc;
3 clear;
4
5 a=imread('cameraman.tif'); % reading the image
6 a=im2double(a); % normalizing the instensity values to lie between 0 and 1
7
8 ref=a;
9 ad=imnoise(a,'gaussian',0.01); % adding Gaussian noise of mean zero and variance
   0.01
10 timestep=0.2; % timestep size used in numerical approximation
11 Niter=60; % number of iterations
12
13 sigma = [0.1, 1, 3]; % Sigma - smoothing parameter
14 lambda = [0.001, 0.01, 0.1, 1, 10]; % Lambda - contrast parameter
15
16 subplotno = 0;
17 for i=1:3
18     for j=1:5
19         b = eed(ad,sigma(i),lambda(j),timestep,Niter,0,1); % Edge Enhancing
           function
20         % Display the image in a subplot
21         subplotno = subplotno+1;
22         subplot(3, 5, subplotno); % 3 rows, 5 columns of subplots
23         imshow(b);
24         title(['sigma = ',num2str(sigma(i)),' ', lambda = ', num2str(lambda(j))]);
25     end
26 end
27 sgttitle('EED Model- contrast parameter lambda & smoothing parameter sigma relation')
28
29 % Arguments
30 % 1 is the noisy image,
31 % 2 is the scale - (variance in Gaussian),
32 % 3 is the lambda value = contrast parameter,
33 % 4 is the timestep size, 5 is the no of iterations,
34 % 6 is the value to show the plot,
35 % 7 is the w value used in numerical approximation
36 % 8 corresponding to choice of the numerical scheme.
```

Output:

EED Model- contrast parameter λ & smoothing parameter σ relation



Figure 5: Relation b/w sigma and lambda for EED model

-
5. From the above findings, can you comment anything on the best stopping time for the respective models?

The best stopping time is the one that gives a good balance between noise reduction and edge preservation for our input images. It can be found by experimenting the above models with different stopping times and finding their PSNR values to get an idea. Stopping time corresponding to higher PSNR value is can be considered a good stopping time.