IMAGE SMOOTHING USING ANISOTROPIC DIFFUSION FILTER

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PROBLEM STATEMENT

Adaptive denoising process by means of anisotropic diffusion filtering.

MOTIVATION

Denoising an image with linear filters such as Gaussian filters is conceptually easy, however, the image details and edges are degraded, resulting in a blurry denoised image. But the anisotropic nonlinear diffusion method reduces noise in flat regions and preserves edges to a greater degree.

THEORY

Diffusion is a physical process which aims at minimizing differences in the spatial concentration u(x,t) of a substance.

The process can be described by two equations:

- Fick's law: $j = -g\nabla u$ (j is diffusion flux, g is diffusivity constant and ∇u is concentration gradient)
- Continuity equation : $\partial_t u = -\text{div } j$

This leads to the diffusion equation $\partial_t u = \text{div} (g \cdot \nabla u)$

THEORY

 $\partial_t \mathbf{u} = \text{div } (\mathbf{g} \cdot \nabla \mathbf{u}) \text{ in this equation:}$

- If g=1 it is known as isotropic or linear diffusion
- If g is a function of u then it is called non linear diffusion
- If g is matrix-valued then it leads to process where diffusion is different in different directions. This is called anisotropic diffusion
- Perona-Malik model leads to less smoothing in locations of strong edge information.
- We use gradient norm as an edge detector, diffusivity should decrease with increasing with $|\nabla u|$.

$$g(|\nabla u|) = \frac{1}{\sqrt{1 + |\nabla u|^2/\lambda^2}}$$

THEORY

Perona and Malik (1987) formulated NLDF(Non linear diffusion filter) in which they replaced the diffusion constant g in the equation $t = div (g \cdot \nabla u)$ with a scalar valued function of gradient ∇u of the grey levels in the image. The diffusion equation then reads

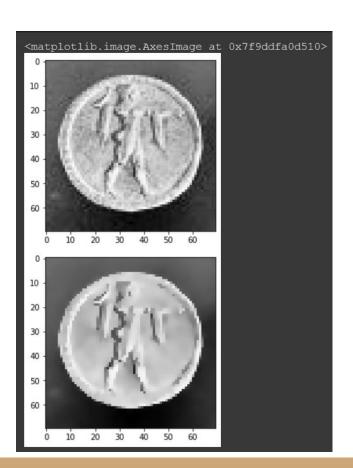
$$\partial_t u = div \left(g\left(|\nabla u| \right) \nabla u \right)$$

```
import numpy as np
import warnings
import cv2
def anisodiff(img,niter=1,kappa=50,gamma=0.1,step=(1.,1.),option=1,ploton=True):
            kappa - conduction coefficient 20-100 ?
            gamma - max value of .25 for stability
           step - tuple, the distance between adjacent pixels in (y,x)
            option - 1 Perona Malik diffusion equation No 1(high contrast over low contrast)
                    2 Perona Malik diffusion equation No 2(wider regions over smaller ones)
            ploton - if True, the image will be plotted on every iteration
                    - diffused image.
    kappa controls conduction as a function of gradient.
    gamma controls speed of diffusion
    step is used to scale the gradients
```

```
if img.ndim == 3:
    warnings.warn("Only grayscale images allowed, converting to 2D matrix")
    img = img.mean(2)
img = img.astype('float32')
imgout = img.copy()
deltaS = np.zeros like(imgout)
deltaE = deltaS.copy()
NS = deltaS.copy()
EW = deltaS.copy()
gS = np.ones like(imgout)
qE = qS.copy()
if ploton:
    import pylab as pl
    fig = pl.figure(figsize=(20,5.5), num="Anisotropic diffusion")
    ax1,ax2 = fig.add subplot(1,2,1),fig.add subplot(1,2,2)
    ax1.imshow(img,interpolation='nearest')
    ih = ax2.imshow(imgout,interpolation='nearest',animated=True)
    ax1.set title("Original image")
    fig.canvas.draw()
```

```
for ii in range (niter):
    deltaS[:-1,: ] = np.diff(imgout,axis=0)
    deltaE[: ,:-1] = np.diff(imgout,axis=1)
    if option == 1:
        qS = np.exp(-(deltaS/kappa)**2.)/step[0]
        gE = np.exp(-(deltaE/kappa)**2.)/step[1]
    elif option == 2:
        gS = 1./(1.+(deltaS/kappa)**2.)/step[0]
        qE = 1./(1.+(deltaE/kappa)**2.)/step[1]
    E = qE*deltaE
    S = qS*deltaS
    # subtract a copy that has been shifted 'North/West' by one pixel
    NS[:] = S
    EW[:] = E
    NS[1:,:] -= S[:-1,:]
    EW[:,1:] -= E[:,:-1]
    imgout += gamma*(NS+EW)
```

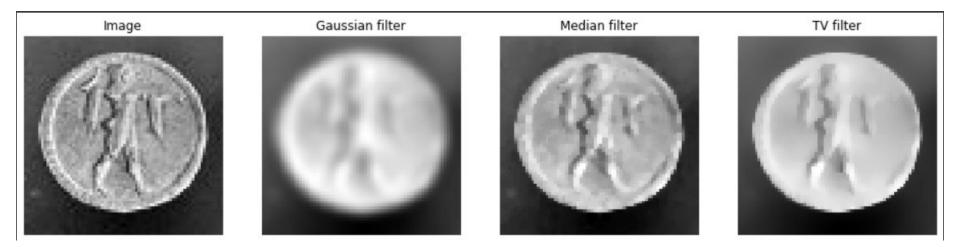
```
if ploton:
         iterstring = "Iteration %i" %(ii+1)
         ih.set data(imgout)
         ax2.set title(iterstring)
         fig.canvas.draw()
         # sleep(0.01)
 return imgout
import matplotlib
%matplotlib inline
import matplotlib.pyplot as plt
#from scipy.misc import imread
#im = imread("lenna.png")
from matplotlib.pyplot import imread
#im =coins[10:80, 300:370]
#im = lenna()[..., 0]
result = anisodiff(im, niter=10, kappa=25)
plt.imshow(im, cmap="Greys r")
plt.figure()
plt.imshow(result, cmap="Greys r")
```



```
import numpy as np
import matplotlib.pyplot as plt
from skimage import data
from skimage import filters
from skimage import restoration

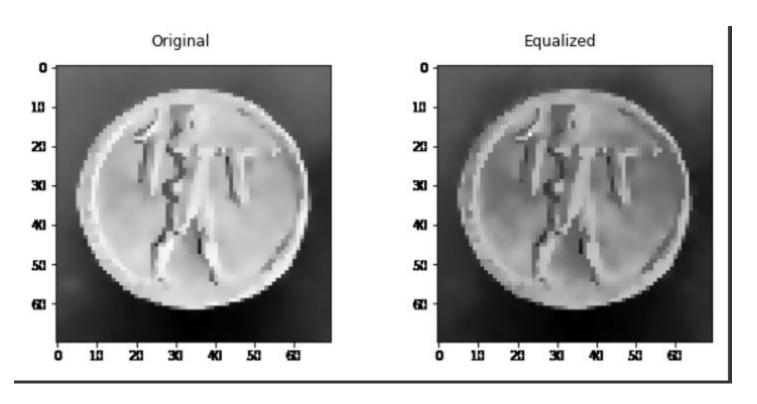
coins = data.coins()
gaussian_filter_coins = filters.gaussian(coins, sigma=2)
med_filter_coins = filters.median(coins, np.ones((3, 3)))
tv_filter_coins = restoration.denoise_tv_chambolle(coins, weight=0.1)
```

```
plt.figure(figsize=(16, 4))
plt.subplot(141)
plt.imshow(coins[10:80, 300:370], cmap='gray', interpolation='nearest')
plt.axis('off')
plt.title('Image')
plt.subplot(142)
plt.imshow(gaussian filter coins[10:80, 300:370], cmap='gray',
           interpolation='nearest')
plt.axis('off')
plt.title('Gaussian filter')
plt.subplot(143)
plt.imshow(med filter coins[10:80, 300:370], cmap='gray',
           interpolation='nearest')
plt.axis('off')
plt.title('Median filter')
plt.subplot(144)
plt.imshow(tv filter coins[10:80, 300:370], cmap='gray',
           interpolation='nearest')
plt.axis('off')
plt.title('TV filter')
plt.show()
```



```
import numpy as np
import cv2
import json
from matplotlib import pyplot as plt
def read this(image file, gray scale=False):
    image src = cv2.imread(image file)
    if gray scale:
        image src = cv2.cvtColor(image src, cv2.COLOR BGR2GRAY)
    else:
        image src = cv2.cvtColor(image src, cv2.COLOR BGR2RGB)
    return image src
```

```
def equalize this(image file, with plot=False, gray scale=False):
    image src = read this(image file=image file, gray scale=gray scale)
    if not gray scale:
        r image, g image, b image = cv2.split(image src)
        r image eq = cv2.equalizeHist(r image)
        g image eq = cv2.equalizeHist(g image)
        b image eq = cv2.equalizeHist(b image)
        image eq = cv2.merge((r image eq, g image eq, b image eq))
        cmap val = None
        image eq = cv2.equalizeHist(image src)
        cmap val = 'gray'
    if with plot:
        fig = plt.figure(figsize=(10, 20))
        ax1 = fig.add subplot(2, 2, 1)
        ax1.axis("off")
        ax1.title.set text('Original')
       ax2 = fig.add subplot(2, 2, 2)
        ax2.axis("off")
        ax2.title.set text("Equalized")
        ax1.imshow(image src, cmap=cmap val)
        ax2.imshow(image eq, cmap=cmap val)
    return image eq
equalize_this(image_file='coins.png', with_plot=True)
```



```
import cv2
import numpy as np
x=cv2.imread('coins.png')
y=cv2.imread('coinsbb.png')
def compute psnr(img1, img2):
    img1 = img1.astype(np.float64) / 255.
    img2 = img2.astype(np.float64) / 255.
   mse = np.mean((img1 - img2) ** 2)
    if mse == 0:
        return "Same Image"
    return 10 * math.log10(1. / mse)
print(compute psnr(x,y))
```

```
import cv2
import numpy as np
import math
z=cv2.imread('coins.png')
r=cv2.imread('gaussb.png')
def compute psnr(img1, img2):
    img1 = img1.astype(np.float64) / 255.
    img2 = img2.astype(np.float64) / 255.
    mse = np.mean((img1 - img2) ** 2)
    if mse == 0:
        return "Same Image"
    return 10 * math.log10(1. / mse)
print(compute psnr(z,r))
```

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from google.colab.patches import cv2 imshow
img= cv2.imread('coins.png')
img1=cv2.imread('coinsbb.png')
images=np.concatenate((img,img1),axis=1)
cv2 imshow(images)
cv2.waitKey(0)
cv2.destroyAllWindows()
gray img=cv2.cvtColor(img,cv2.COLOR BGR2GRAY)
gray img1=cv2.cvtColor(img1,cv2.COLOR BGR2GRAY)
hist=cv2.calcHist(gray img, [0], None, [256], [0, 256])
hist1=cv2.calcHist(gray img1, [0], None, [256], [0, 256])
plt.subplot(121)
plt.title("Image1")
plt.xlabel('bins')
plt.ylabel("No of pixels")
plt.plot(hist)
plt.subplot(122)
plt.title("Image2")
plt.xlabel('bins')
plt.ylabel("No of pixels")
plt.plot(hist1)
plt.show()
```

```
gray img eqhist=cv2.equalizeHist(gray img)
gray img1 eqhist=cv2.equalizeHist(gray img1)
hist=cv2.calcHist(gray img eqhist, [0], None, [256], [0, 256])
hist1=cv2.calcHist(gray img1 eqhist, [0], None, [256], [0,256])
plt.subplot(121)
plt.plot(hist)
plt.subplot(122)
plt.plot(hist1)
plt.show()
eqhist images=np.concatenate((gray img eqhist,gray img1 eqhist),axis=1)
cv2 imshow(eqhist images)
cv2.waitKey(0)
cv2.destroyAllWindows()
clahe=cv2.createCLAHE(clipLimit=40)
gray img clahe=clahe.apply(gray img eqhist)
gray img1 clahe=clahe.apply(gray img1 eqhist)
images=np.concatenate((gray img clahe, gray img1 clahe), axis=1)
cv2 imshow(images)
cv2.waitKey(0)
cv2.destroyAllWindows()
t.h = 80
max val=255
```

```
ret, o1 = cv2.threshold(gray_img_clahe, th, max_val, cv2.THRESH_BINARY)

cv2.putText(o1,"Thresh_Binary",(40,100),cv2.FONT_HERSHEY_SIMPLEX,2,(255,255,255),3,cv2.LINE_AA)

ret, o2 = cv2.threshold(gray_img_clahe, th, max_val, cv2.THRESH_BINARY_INV)

cv2.putText(o2,"Thresh_Binary_inv",(40,100),cv2.FONT_HERSHEY_SIMPLEX,2,(255,255,255),3,cv2.LINE_AA)

ret, o3 = cv2.threshold(gray_img_clahe, th, max_val, cv2.THRESH_TOZERO)

cv2.putText(o3,"Thresh_Tozero",(40,100),cv2.FONT_HERSHEY_SIMPLEX,2,(255,255,255),3,cv2.LINE_AA)

ret, o4 = cv2.threshold(gray_img_clahe, th, max_val, cv2.THRESH_TOZERO_INV)

cv2.putText(o4,"Thresh_Tozero_inv",(40,100),cv2.FONT_HERSHEY_SIMPLEX,2,(255,255,255),3,cv2.LINE_AA)

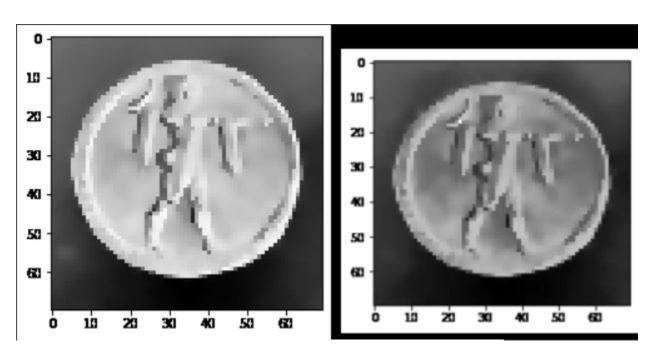
ret, o5 = cv2.threshold(gray_img_clahe, th, max_val, cv2.THRESH_TRUNC)

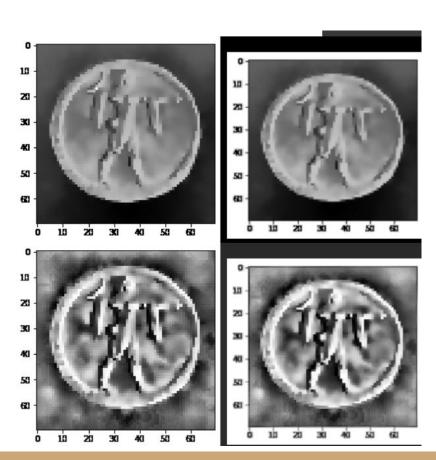
cv2.putText(o5,"Thresh_trunc",(40,100),cv2.FONT_HERSHEY_SIMPLEX,2,(255,255,255),3,cv2.LINE_AA)

ret, o6= cv2.threshold(gray_img_clahe, th, max_val, cv2.THRESH_OTSU)

cv2.putText(o6,"Thresh_OSTU",(40,100),cv2.FONT_HERSHEY_SIMPLEX,2,(255,255,255),3,cv2.LINE_AA)
```

```
final=np.concatenate((01,02,03),axis=1)
final1=np.concatenate((04,05,06),axis=1)
cv2.imwrite("Image1.jpg", final)
cv2.imwrite("Image2.jpg", final1)
gray image = cv2.imread('coins.png',0)
gray image1 = cv2.imread('coinsbb.png',0)
thresh1 = cv2.adaptiveThreshold(gray image, 255, cv2.ADAPTIVE THRESH MEAN C, cv2.THRESH BINARY, 11, 2)
thresh2 = cv2.adaptiveThreshold(gray image, 255, cv2.ADAPTIVE THRESH MEAN C, cv2.THRESH BINARY, 31, 3)
thresh3 = cv2.adaptiveThreshold(gray image, 255, cv2.ADAPTIVE THRESH GAUSSIAN C, cv2.THRESH BINARY, 13, 5)
thresh4 = cv2.adaptiveThreshold(gray image, 255, cv2.ADAPTIVE THRESH GAUSSIAN C, cv2.THRESH BINARY, 31, 4)
thresh11 = cv2.adaptiveThreshold(gray image1, 255, cv2.ADAPTIVE THRESH MEAN C, cv2.THRESH BINARY, 11, 2)
thresh21 = cv2.adaptiveThreshold(gray image1, 255, cv2.ADAPTIVE THRESH MEAN C, cv2.THRESH BINARY, 31, 5)
thresh31 = cv2.adaptiveThreshold(gray image1, 255, cv2.ADAPTIVE THRESH GAUSSIAN C, cv2.THRESH BINARY, 21,5)
thresh41 = cv2.adaptiveThreshold(gray image1, 255, cv2.ADAPTIVE THRESH GAUSSIAN C, cv2.THRESH BINARY, 31, 5)
final=np.concatenate((thresh1,thresh2,thresh3,thresh4),axis=1)
final1=np.concatenate((thresh11,thresh21,thresh31,thresh41),axis=1)
cv2.imwrite('rect.jpg',final)
cv2.imwrite('rect1.jpg',final1)
gray image = cv2.imread('coins.png',0)
gray image1 = cv2.imread('coinsbb.png',0)
ret,thresh1 = cv2.threshold(gray image,0, 255, cv2.THRESH BINARY+cv2.THRESH OTSU)
ret,thresh2 = cv2.threshold(gray image1,0, 255, cv2.THRESH BINARY+cv2.THRESH OTSU)
cv2.imwrite('rect.jpeg',np.concatenate((thresh1,thresh2),axis=1))
```





FUTURE SCOPE

Anisotropic methods of diffusion degrades the fine structure and reduces the resolution of the image. In future we can use various quality enhancement methods and adaptive learning filters.

It is clear, however, that nonlinear diffusion filtering is a young field which has certainly not reached its final state yet.

CONCLUSION

As the performed denoising experiments and the method comparison provided encouraging results.

The anisotropic diffusion technique gives better enhanced image than Gaussian filter and this result is backed by SNR. Because of this method's strong edge-preserving character, it can be successfully used for edge detection or computer vision tasks like object detection, satellite image enhancement.

<u>REFERENCES</u>

- 1)"On the choice of the parameters for anisotropic diffusion in image processing,"C. Tsiotsios, M. Petrou.
- 2)"Adaptive Image Denoising Method Based on Diffusion Equation and Deep Learning," S.Ma, C.Zhang, Journal of Robotics, vol.2022, Article ID 7115551, 9 pages, 2022.
- 3) "Variational methods for computer vision," Prof.Dr. Daniel Cremers.

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THANK YOU