

Codes for each problem are available at https://github.com/kjoyce/inverse_problems/tree/master/homework04/codes

1.

(a) Derive the formulas for the UPRE analogous to (3.18) for GCV. Add lines of code to `Deblur2dPeriodic.m` so that it implements UPRE.

Assuming the derivation from the GCV formulation, we have the following forms for $\|\mathbf{A}\mathbf{x}_\alpha - \mathbf{b}\|^2$ and $\text{tr}(\mathbf{A}\mathbf{A}_\alpha)$,

$$U(\alpha) = \|\mathbf{A}\mathbf{x}_\alpha - \mathbf{b}\|^2 + 2\sigma^2 \text{tr}(\mathbf{A}\mathbf{A}_\alpha) = \sum_{i,j}^n \frac{\alpha^2 \hat{\mathbf{B}}_{i,j}}{(|\hat{\mathbf{a}}_s|_{ij}^2 + \alpha)^2} + 2\sigma^2 \sum_{i,j}^n \frac{|\hat{\mathbf{a}}_s|_{ij}^2}{|\hat{\mathbf{a}}_s|_{ij}^2 + \alpha}.$$

where $\hat{\mathbf{B}} = \text{DFT}(\mathbf{B})$ and $\hat{\mathbf{a}}_s = n^2 \text{DFT}(\mathbf{a}_s)$. The Matlab codes implementing this are as follows:

```
upre_fn = @(a) a^2*sum(sum((abs(bhat/nx).^2)./(abs(ahat).^2+a).^2))+...
    2*sigma^2*sum(sum(abs(ahat).^2./(abs(ahat).^2+a)));
upre_alpha = fminbnd(upre_fn,0,1)
```

(b) Derive the formulas for the DP analogous to (3.18) for GCV. Add lines of code to `Deblur2dPeriodic.m` so that it implements DP regularization parameter selection methods.

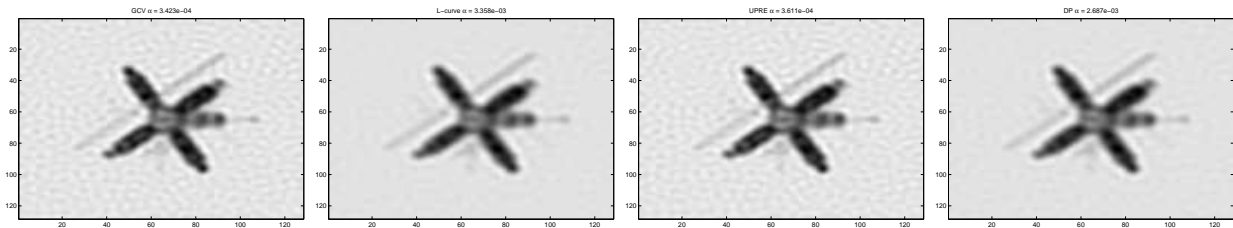
Under similar assumptions as above, we obtain

$$D(\alpha) = \|\mathbf{A}\mathbf{x}_\alpha - \mathbf{b}\|^2 - n^2\sigma^2 = \sum_{i,j}^n \frac{\alpha^2 \hat{\mathbf{B}}_{i,j}}{(|\hat{\mathbf{a}}_s|_{ij}^2 + \alpha)^2} - n^2\sigma^2.$$

The relevant Matlab code is:

```
dp_fn = @(a) (a^2*sum(sum((abs(bhat/nx).^2)./(abs(ahat).^2+a).^2))-n*sigma^2)^2;
dp_alpha = fminbnd(dp_fn,0,1)
```

The reconstructions from these, and the two given parameter selection methods are given in the figure below.



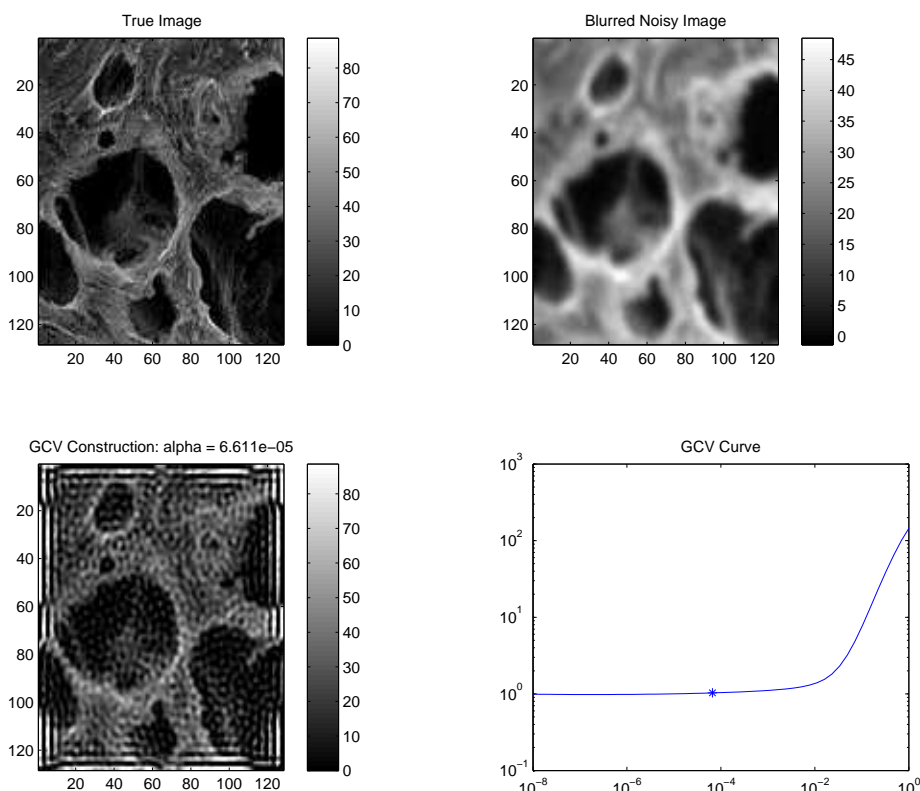
2. Bardsley 3.11. *An example in which the periodic boundary conditions assumption is poor.* Implement Tikhonov regularization with periodic a boundary condition and GCV stopping rule on the example given in `PeriodicBCtest.m`. Note that the blurred image is the central 128×128 pixels of a 256×256 image and hence does not contain boundary artifacts from the periodic boundary conditions assumed for the forward model. Perform the deblurring on the 128×128 subimage. Plot a picture of the deblurred image.

Solution:

The relevant codes for implementing this are given below:

```
n = nx*ny;
ahat = fft2(fftshift(kernel));
bhat = fft2(b);
G_fn=@(a)(sum(sum((a^2*abs(bhat).^2)./(abs(ahat).^2+a).^2)))/...
    (n-sum(sum(abs(ahat).^2./(abs(ahat).^2+a))))^2;
gcv_alpha = fminbnd(G_fn,0,1);
xalpha = @(a) real(ifft2((conj(ahat)./(abs(ahat).^2+a).*bhat)));
```

A plot of the reconstruction is given below. Note the severe boundary artifacts.



□

3. Modify `Deblur2DataDriven.m` so that the truncated Landweber iteration, introduced in Chapter 2, is used for solving the deblurring problem. Use the DP stopping rule, i.e. choose the first k such that $\|\mathbf{A}\mathbf{x}_k - \mathbf{b}\|^2 \leq n^2\sigma^2$.

Solution:

The relevant codes for implementing this are given below.

```
x = zeros(nx,ny);
tau = .8;% * 1/max(ahat(:));
figure()
```

```

n = 0;
while( true )
    n = n+1;
    resid = DA_mult(x,ahat)-b;
    x = x - tau*AtDt_mult(resid,ahat);
    if norm(resid)^2 <= nx*ny*noise^2; break; end; % end if you actually can
end;
end

```

```

function DAx = DA_mult(x,ahat)
Ax = real(ifft2(ahat.*fft2(x)));
[nx, ny] = size(x);
DAx = Ax(nx/4+1:3*nx/4,ny/4+1:3*ny/4);

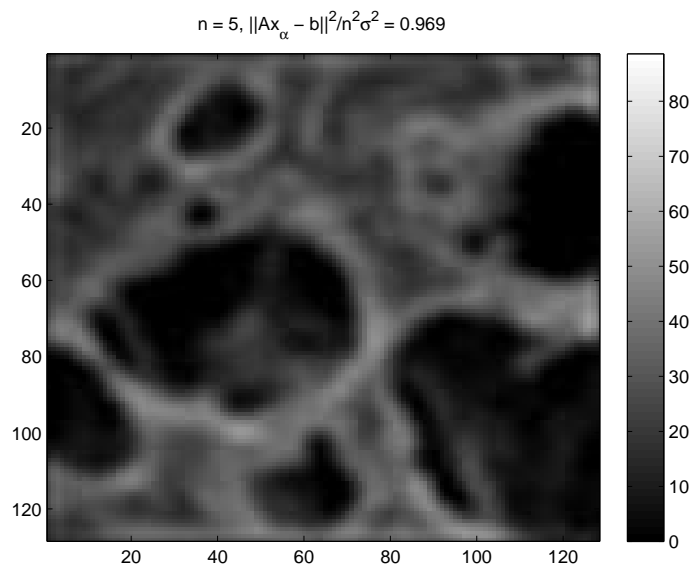
```

```

function AtDtx = AtDt_mult(x,ahat)
[nnx, nny] = size(x);
Dtx = padarray(x, [nnx/2, nny/2]);
AtDtx = real(ifft2(conj(ahat).*fft2(Dtx)));

```

An image of the resulting reconstruction is given below.



□