ECE253, HW3, Report

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Problem 1

In [ ]:

```
### Matlab Code

%% ECE253, HW3, Problem 1, Version 2
% William Argus A12802324
%% setup
clc;
clear all;
close all;

image = imread('geisel.jpg');
imageGray = rgb2gray(image);
te = 130
edges = cannyEdgeDetection(imageGray, te);
figure(3);
imshow(im2uint8(edges/255));
title('Final edge image after thresholding', 'FontSize', 16);
%% function
function imageEdges = cannyEdgeDetection(imageGray, te)
    %% Part 1
    k = (1/159)*[2 4 5 4 2; 4 9 12 9 4; 5 12 15 12 5; 4 9 12 9 4
; 2 4 5 4 2];
    imageSmooth = conv2(imageGray, k);
    imageSmooth = im2uint8(imageSmooth/255);

    %% Part 2
```

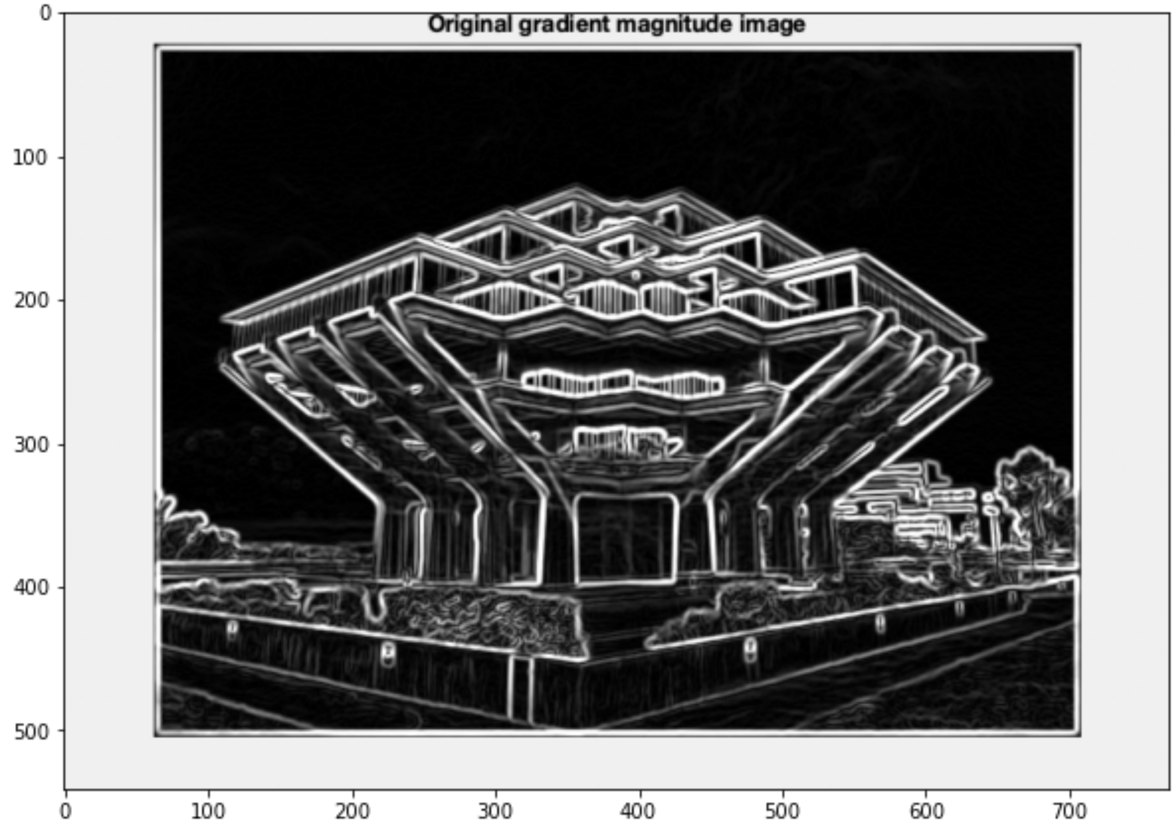
```
%% Part 2

kx = [-1 0 1; -2 0 2; -1 0 1];
ky = [-1 -2 -1; 0 0 0; 1 2 1];

gX = conv2(imageSmooth, kx);
gY = conv2(imageSmooth, ky);
absGradient = sqrt(gX.^2 + gY.^2);
gX(gX == 0) = 0.0001;
angleGradient = atand(gY./gX);
figure(1);
imshow(im2uint8(absGradient/255));
title('Original gradient magnitude image', 'FontSize', 16);

%% Part 3
angleGradient(-22.5 <= angleGradient & 22.5 > angleGradient)
= 0;
angleGradient(-67.5 <= angleGradient & -22.5 > angleGradient
) = -45;
angleGradient(67.5 > angleGradient & 22.5 <= angleGradient)
= 45;
angleGradient(-67.5 > angleGradient) = 90;
angleGradient(67.5 <= angleGradient) = 90;

%for each pixel
sz = size(absGradient);
pixel1=0;
pixel2=0;
for i = 2:sz(1)-1
   for j = 2:sz(2)-1
       %get gradient direction to pick comparison pixels
       if angleGradient(i,j) == 90
           pixel1 = absGradient(i-1,j);
           pixel2 = absGradient(i+1,j);
       elseif angleGradient(i,j) == -45
           pixel1 = absGradient(i-1,j-1);
           pixel2 = absGradient(i+1,j+1);
       elseif angleGradient(i,j) == 0
           pixel1 = absGradient(i,j+1);
           pixel2 = absGradient(i,j-1);
       elseif angleGradient(i,j) == 45
           pixel1 = absGradient(i-1,j+1);
           pixel2 = absGradient(i+1,j-1);
       else
           print("ERROR!!");
```

```
            end
            if absGradient(i,j) > pixel1 && absGradient(i,j) > pi
xel2
                nothing=0;
            else
                absGradient(i,j)=0;
            end
        end
    end

    figure(2);
    imshow(im2uint8(absGradient/255));
    title('Image after NMS', 'FontSize', 16);

    %% Part 4

    absGradient(absGradient < te) =0;
    imageEdges = absGradient;
end
```

In [194]:

```
#Results
import matplotlib.pyplot as plt

P1_1 = plt.imread('P1.1.png')
P1_2 = plt.imread('P1.2.png')
P1_3 = plt.imread('P1.3.png')

plt.figure(figsize = (10,10))
plt.imshow(P1_1)
plt.figure(figsize = (10,10))
plt.imshow(P1_2)
plt.figure(figsize = (10,10))
plt.imshow(P1_3)

print('Value of te used to product final image: 130')
print('This ')
```

```
Value of te used to product final image: 130
```


Original gradient magnitude image
0
100
200
300
400
500
0
100
200
300
400
500
600
700

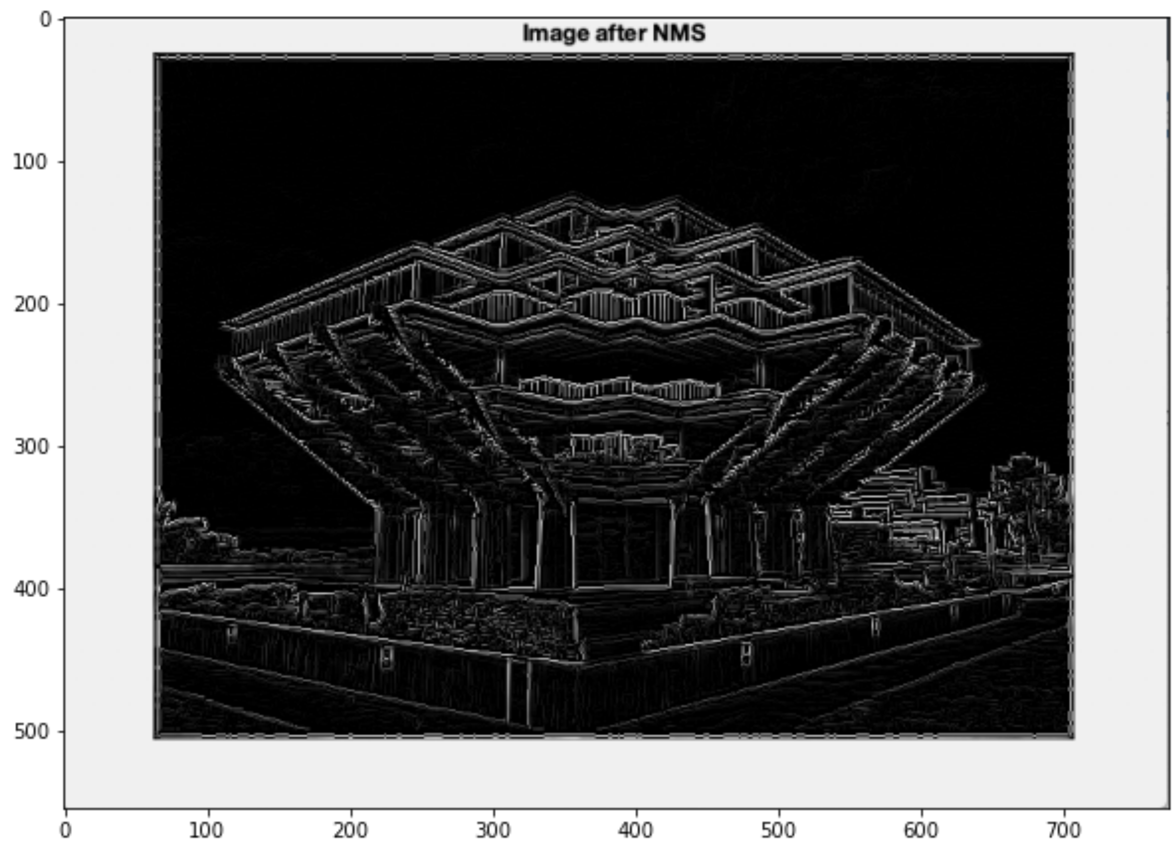
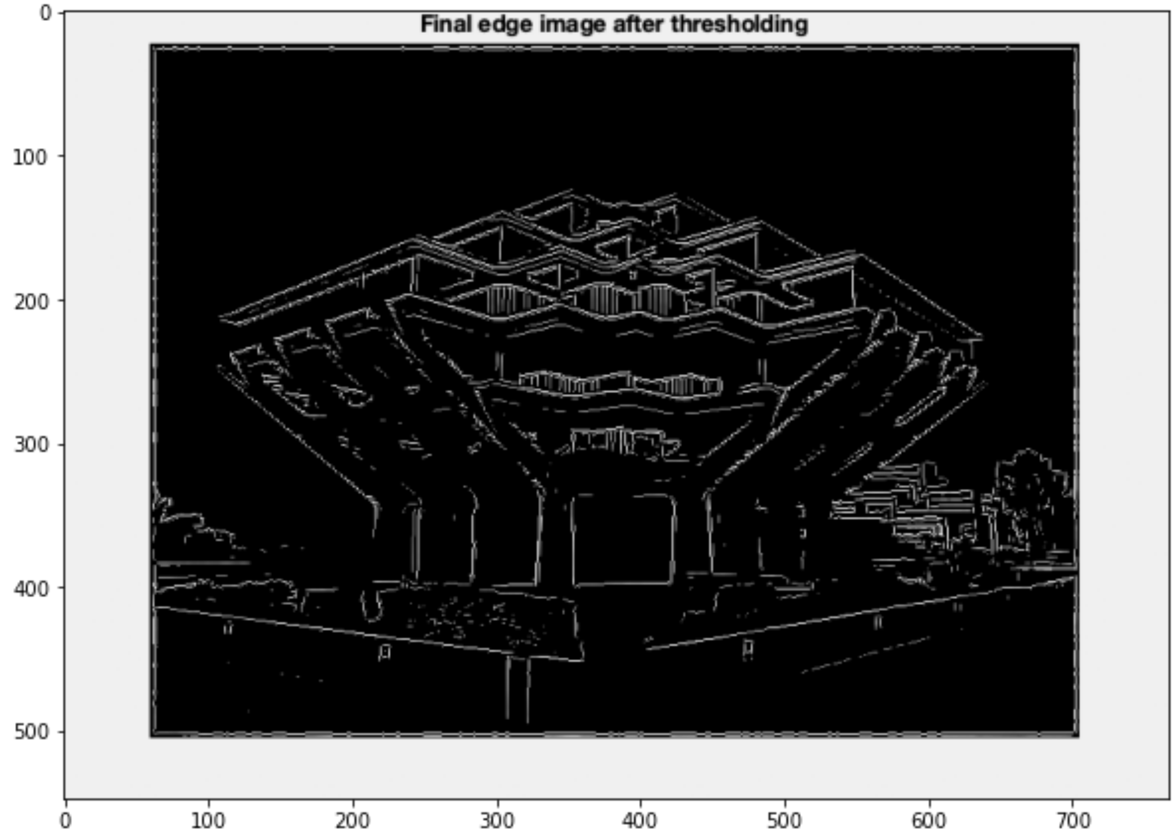


Image after NMS
0
100
200
300
400
500
0
100
200
300
400
500
600
700



Problem 2

Problem 2 (i)

In [ ]:

```
### Matlab Code for (i)

%% ECE253, HW3, Problem 2i, Version 1
% William Argus A12802324
%% setup
clc;


image = imread('Car.tif');
figure(1);
imshow(image);
title('Unpadded original image')
colorbar;
%%
sz = size(image);
padsize1 = (512-sz(1))/2 +1;
padsize2 = (512-sz(2))/2 +1;
```

```
paddedImage = im2uint8(zeros(512,512));


paddedImage((padsize1+1):(padsize1+sz(1)), (padsize2+1):(padsize
2+sz(2))) = image;
%figure(2);
%imshow(paddedImage);

imFFT = fft2(paddedImage);
%test = ifft2(imFFT);
imFFT = fftshift(imFFT);
%figure(4);
%imshow(im2uint8(test/255));
figure(2)
imagesc(-256:255,-256:255,log(abs(imFFT)));
colorbar;
title('2D DFT log-magnitude of original image');
xlabel('u');
ylabel('v');

[u,v] = meshgrid(-256:255);

%iterate through all possible u values, then through all possibl
e v values,
%then for each (u,v), calcuate Dk
%then Hnr for each (u,v)?
%since there is 4 bursts, need 4 pairs of coordinates for the bu
rsts

%calculate Hnr
Hnr = ones(512,512);
Do = 20
n = 2
uv = [83, -175; 83, -90; 90, 81; 90, 170]
for k = 1:4
    uk = uv(k,1);
    vk = uv(k,2);
    %Dpk = zeros(512,512);
    %Dmk = zeros(512,512);
    Dpk = ((u - uk).^2 + (v - vk).^2).^.5;
    Dmk = ((u + uk).^2 + (v + vk).^2).^.5;

    term1 = ( 1+ (Do.*(Dpk.^-1)).^(2*n) ).^-1;
    term2 = ( 1+ (Do.*(Dmk.^-1)).^(2*n) ).^-1;
    temp = term1.*term2;
```

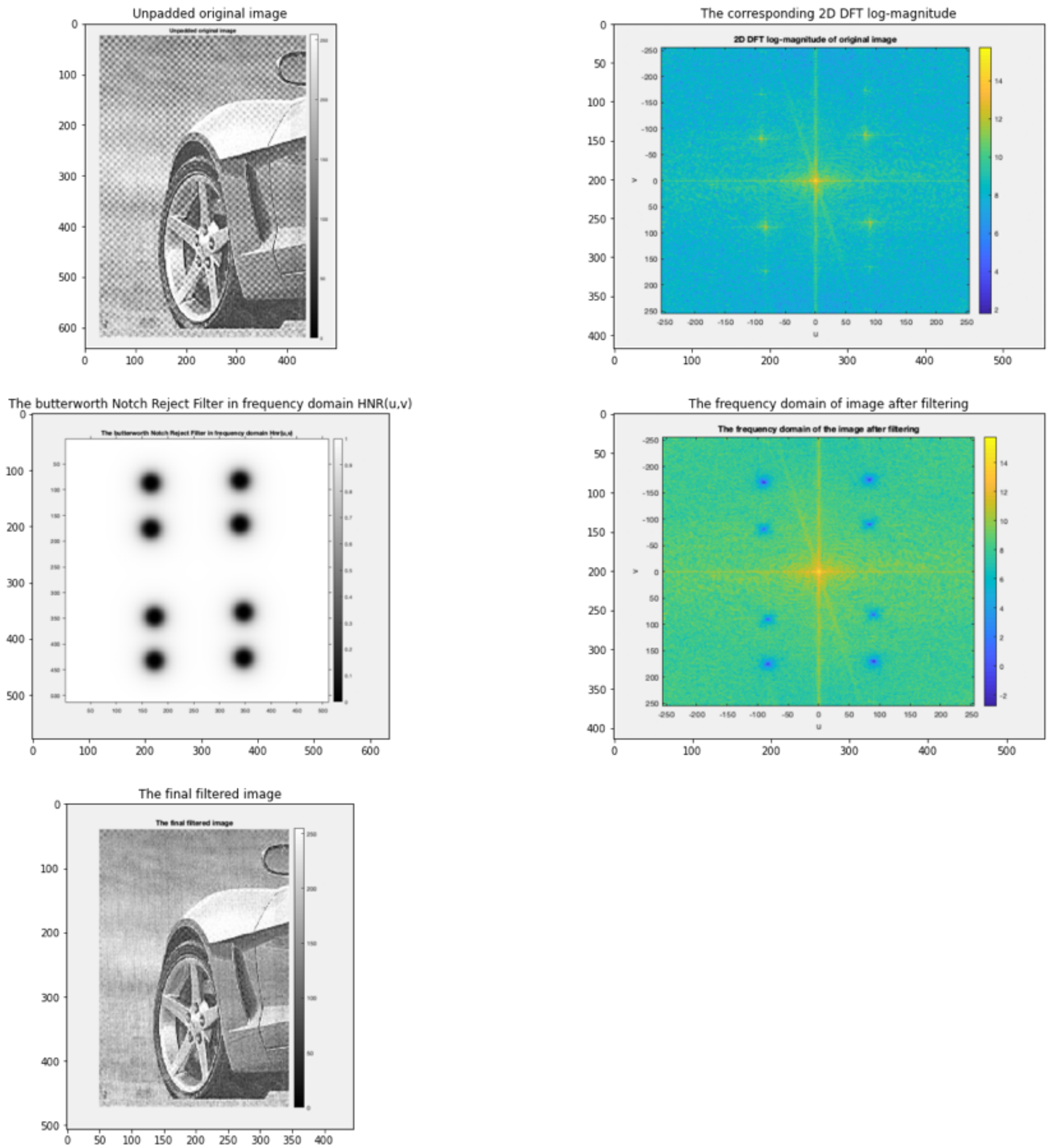
```
    Hnr = Hnr.*temp;
end

figure(3);
imshow(Hnr);
colorbar;
title('The butterworth Notch Reject Filter in frequency domain H
nr(u,v)');
h = gca;
set(h, 'Visible', 'On')

freqImage = Hnr.*imFFT;
figure(4);
imagesc(-256:255,-256:255,log(abs(freqImage)));
colorbar;
title('The frequency domain of the image after filtering');
xlabel('u');
ylabel('v');

unshift = ifftshift(freqImage);
resultPadded = ifft2(unshift);
%unpad image
result = resultPadded((padsize1+1):(padsize1+sz(1)), (padsize2+1
):(padsize2+sz(2)));
figure(5);
imshow(im2uint8(result/255));
colorbar;
title('The final filtered image');
```

In [206]:

```
#Results
import matplotlib.pyplot as plt

P2i_1 = plt.imread('P2i.1.png')
P2i_2 = plt.imread('P2i.2.png')
P2i_3 = plt.imread('P2i.3.png')
P2i_4 = plt.imread('P2i.4.png')
P2i_5 = plt.imread('P2i.5.png')


plt.figure(figsize = (20,20))
plt.subplot(321)
plt.imshow(P2i_1)
plt.title('Unpadded original image')
plt.subplot(322)
plt.imshow(P2i_2)
plt.title('The corresponding 2D DFT log-magnitude')
plt.subplot(323)
plt.imshow(P2i_3)
plt.title('The butterworth Notch Reject Filter in frequency doma
in HNR(u,v)')
plt.subplot(324)
plt.imshow(P2i_4)
plt.title('The frequency domain of image after filtering')
plt.subplot(325)
plt.imshow(P2i_5)
plt.title('The final filtered image')
```

Out[206]:

```
Text(0.5, 1.0, 'The final filtered image')
```



Do = 20 n = 2 u, v = (8 terms below) u1 = 83, v1 = -175 u2 = 83, v2 = -90 u3 = 90, v3 = 81 u4 = 90, v4 = 170

Problem 2 (ii)

In [ ]:

```
### Matlab code for (ii)

%% ECE253, HW3, Problem 2ii, Version 1
% William Argus A12802324
```

```matlab
%% setup


image = imread('Street.png');
figure(1);
imshow(image);
title('Unpadded original image')
colorbar;

sz = size(image);
padsize1 = (512-sz(1))/2 +1;
padsize2 = (512-sz(2))/2 +1;
paddedImage = im2uint8(zeros(512,512));

paddedImage((padsize1+1):(padsize1+sz(1)), (padsize2+1):(padsize2+sz(2))) = image;
%figure(2);
%imshow(paddedImage);

imFFT = fft2(paddedImage);
%test = ifft2(imFFT);
imFFT = fftshift(imFFT);
%figure(4);
%imshow(im2uint8(test/255));
figure(2)
imagesc(-256:255,-256:255,log(abs(imFFT)));
colorbar;
title('2D DFT log-magnitude of original image');
xlabel('u');
ylabel('v');

[u,v] = meshgrid(-256:255);
%%
%iterate through all possible u values, then through all possible v values,
%then for each (u,v), calcuate Dk
%then Hnr for each (u,v)?
%since there is 4 bursts, need 4 pairs of coordinates for the bursts

%calculate Hnr
Hnr = ones(512,512);
Do = 50
n = 2
uv = [0, -165; 165, 0;]
```

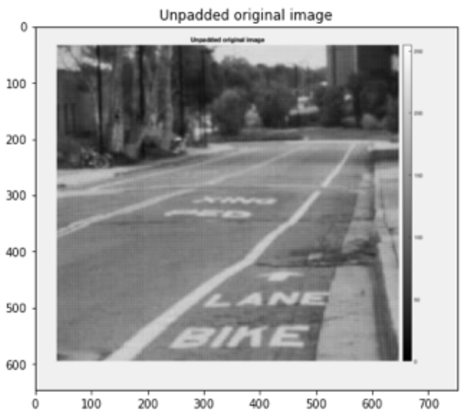
```
for k = 1:2
    uk = uv(k,1);
    vk = uv(k,2);
    Dpk = ((u - uk).^2 + (v - vk).^2).^.5;
    Dmk = ((u + uk).^2 + (v + vk).^2).^.5;

    term1 = ( 1+ (Do.*(Dpk.^-1)).^(2*n) ).^-1;
    term2 = ( 1+ (Do.*(Dmk.^-1)).^(2*n) ).^-1;
    temp = term1.*term2;
    Hnr = Hnr.*temp;
end

figure(3);
imshow(Hnr);
colorbar;
title('The butterworth Notch Reject Filter in frequency domain H
nr(u,v)');
h = gca;
set(h, 'Visible', 'On')

freqImage = Hnr.*imFFT;
figure(4);
imagesc(-256:255,-256:255,log(abs(freqImage)));
colorbar;
title('The frequency domain of the image after filtering');
xlabel('u');
ylabel('v');

unshift = ifftshift(freqImage);
resultPadded = ifft2(unshift);
%unpad image
result = resultPadded((padsize1+1):(padsize1+sz(1)), (padsize2+1
):(padsize2+sz(2)));
figure(5);
imshow(im2uint8(result/255));
colorbar;
title('The final filtered image');
```

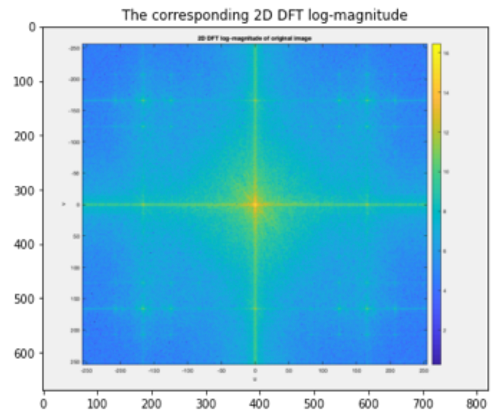
In [207]:

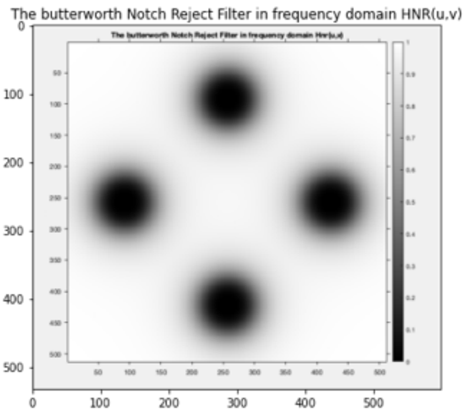
```
#Results
import matplotlib.pyplot as plt

P2ii_1 = plt.imread('P2ii.1.png')
P2ii_2 = plt.imread('P2ii.2.png')
P2ii_3 = plt.imread('P2ii.3.png')
P2ii_4 = plt.imread('P2ii.4.png')
P2ii_5 = plt.imread('P2ii.5.png')

plt.figure(figsize = (20,20))
plt.subplot(321)
plt.imshow(P2ii_1)
plt.title('Unpadded original image')
plt.subplot(322)
plt.imshow(P2ii_2)
plt.title('The corresponding 2D DFT log-magnitude')
plt.subplot(323)
plt.imshow(P2ii_3)
plt.title('The butterworth Notch Reject Filter in frequency doma
in HNR(u,v)')
plt.subplot(324)
plt.imshow(P2ii_4)
plt.title('The frequency domain of image after filtering')
plt.subplot(325)
plt.imshow(P2ii_5)
plt.title('The final filtered image')
```

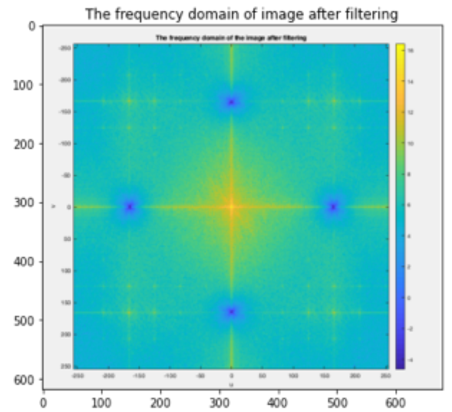
Out[207]:

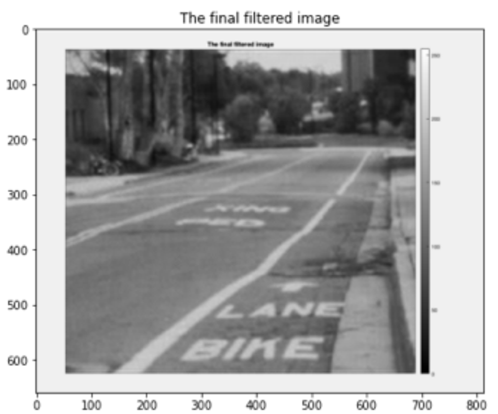
```
Text(0.5, 1.0, 'The final filtered image')
```











Do = 50 n = 2 uv = (4 terms below) u1 = 0, v1 = -165 u2 = 165, v2 = 0

In [ ]:

Problem 3

In [16]:

```
import torch
import torchvision
import torchvision.transforms as transforms
```

In [17]:

```
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Normalize((.5, .5, .5
),(.5, .5, .5))])
trainset = torchvision.datasets.CIFAR10(root='./data', train=Tru
e, download=True,
                                         transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=4
,
                                          shuffle=True, num_work
ers=2)
testset = torchvision.datasets.CIFAR10(root='./data', train=Fals
e,
                                       download=True, transform=
transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=4,
                                         shuffle=False, num_work
ers=2)
classes = ('plane', 'car', 'bird', 'cat',
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [18]:

```python
import matplotlib.pyplot as plt
import numpy as np
# functions to show an image

def imshow(img):
    img = img / 2 + 0.5     # unnormalize
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

# get some random training images
dataiter = iter(trainloader)
images, labels = dataiter.next()

# show images
imshow(torchvision.utils.make_grid(images))
# print labels
print(' '.join('%5s' % classes[labels[j]] for j in range(4)))
```


```
plane   cat  deer   car
```

In [19]:

```
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x


net = Net()
```

In [20]:

```
import torch.optim as optim

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

In [23]:

```python
for epoch in range(2):  # loop over the dataset multiple times
    print('Training, epoch: ', epoch)
    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs; data is a list of [inputs, labels]
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999:    # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Finished Training')
```

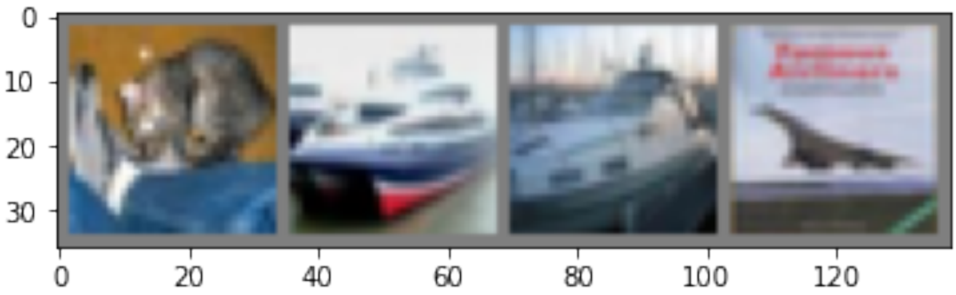
```
Training, epoch:  0
[1,  2000] loss: 2.179
[1,  4000] loss: 1.909
[1,  6000] loss: 1.702
[1,  8000] loss: 1.596
[1, 10000] loss: 1.541
[1, 12000] loss: 1.488
Training, epoch:  1
[2,  2000] loss: 1.400
[2,  4000] loss: 1.408
[2,  6000] loss: 1.368
[2,  8000] loss: 1.338
[2, 10000] loss: 1.314
[2, 12000] loss: 1.287
Finished Training
```

In [24]:

```
PATH = './cifar_net.pth'
torch.save(net.state_dict(), PATH)
```

In [25]:

```
dataiter = iter(testloader)
images, labels = dataiter.next()

# print images
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j
in range(4)))
```




```
GroundTruth:    cat  ship  ship plane
```

In [26]:

```
net = Net()
net.load_state_dict(torch.load(PATH))
```

Out[26]:

```
<All keys matched successfully>
```

In [27]:

```
outputs = net(images)
```

In [29]:

```
_, predicted = torch.max(outputs, 1)

print('Predicted: ', ' '.join('%5s' % classes[predicted[j]]
                              for j in range(4)))
```

```
Predicted:   bird   car   car plane
```

In [30]:

```
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %d %%'
% (
    100 * correct / total))
```

```
Accuracy of the network on the 10000 test images: 53
%
```

In [31]:

```
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs, 1)
        c = (predicted == labels).squeeze()
        for i in range(4):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1


for i in range(10):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

```
Accuracy of plane : 73 %
Accuracy of   car : 68 %
Accuracy of  bird : 38 %
Accuracy of   cat : 45 %
Accuracy of  deer : 49 %
Accuracy of   dog : 25 %
Accuracy of  frog : 60 %
Accuracy of horse : 66 %
Accuracy of  ship : 53 %
Accuracy of truck : 54 %
```

In [32]:

```
device = torch.device("cuda:0" if torch.cuda.is_available() else
"cpu")

# Assuming that we are on a CUDA machine, this should print a CU
DA device:

print(device)
```

```
cuda:0
```

In [33]:

```
net.to(device)
```

Out[33]:

```
Net(
  (conv1): Conv2d(3, 6, kernel_size=(5, 5), stride=(
1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding
=0, dilation=1, ceil_mode=False)
  (conv2): Conv2d(6, 16, kernel_size=(5, 5), stride=
(1, 1))
  (fc1): Linear(in_features=400, out_features=120, b
ias=True)
  (fc2): Linear(in_features=120, out_features=84, bi
as=True)
  (fc3): Linear(in_features=84, out_features=10, bia
s=True)
)
```

In [34]:

```
inputs, labels = data[0].to(device), data[1].to(device)
```

In [ ]:

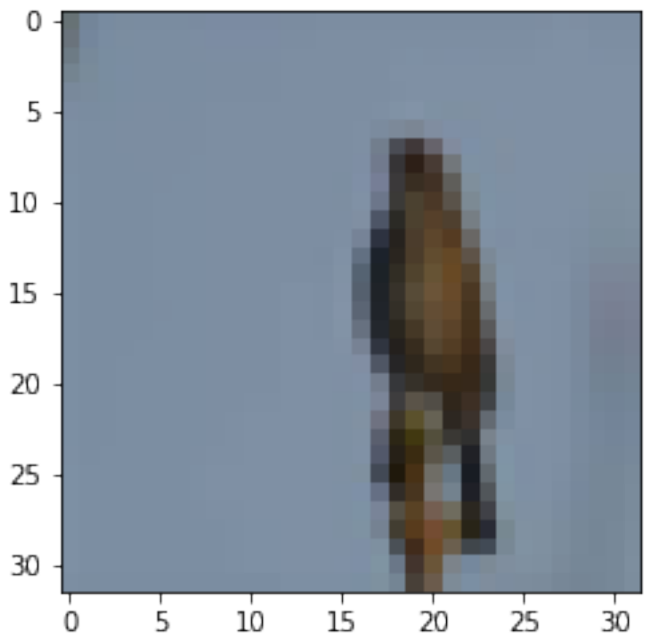
In [ ]:

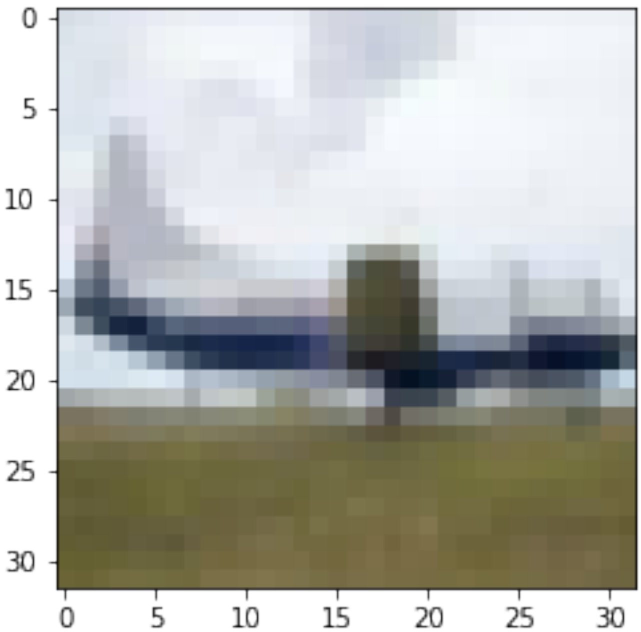
In [ ]:

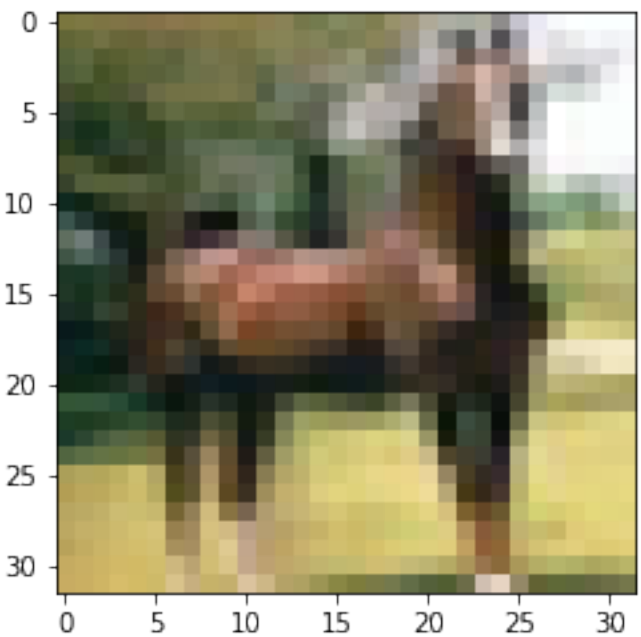
In [67]:

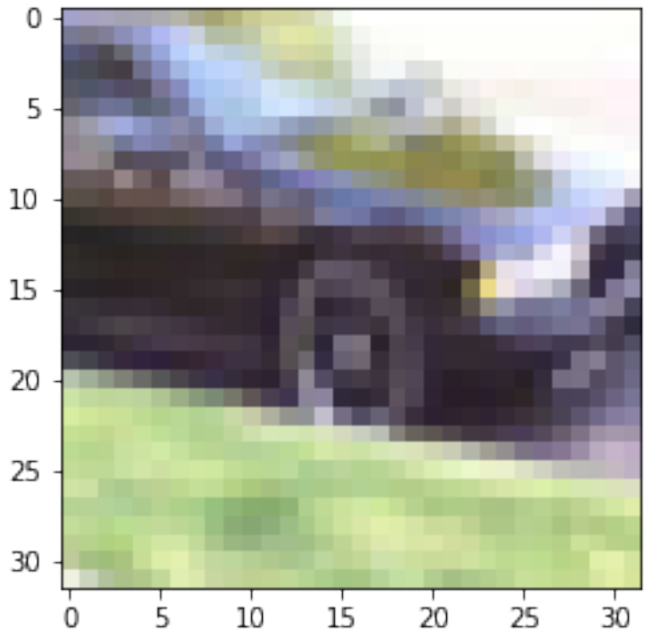
```
numTraining = 0
inputSize = 0
inputsCheck = 0
for i, data in enumerate(trainloader, 0):
    # get the inputs; data is a list of [inputs, labels]
    inputs, labels = data
    inputsCheck = inputs
    inputSize = len(inputs)
    numTraining = numTraining + 1
print('Number of minibatches: ', numTraining)
print('Number of images per batch: ',inputSize)
imshow(inputsCheck[0])
imshow(inputsCheck[1])
imshow(inputsCheck[2])
imshow(inputsCheck[3])
```

```
Number of minibatches:  12500
Number of images per batch:  4
```




0
5
10
15
20
25
30
0
5
10
15
20
25
30


0
5
10
15
20
25
30
0
5
10
15
20
25
30



(ii)

How many images and batches are used to train the network?

12,500 mini-batches loaded in with trainloader. 4 training images per mini-batch, as found in the cell above. Therefore, a total of 50,000 images used to train the network. 1 batch in total since it was mentioned in lecture that the batch refers to all of the images in the training dataset, therefore in this case the entiirety of the training set is one batch divided into mini batches with 4 images in each to be used to train the network.

(iii)

Do we normalize the images? What do we do in the example?

Yes, normalization of the training and test set is necessary in a neural network as the ranges of feature distributions must be the same in order for the network to learn the correct weights. This is because the weights are determined through multiplication of the errors found via backpropogation by the defined learning rate of the network. In the above example, the images are indeed normalized, specifically in the definition of 'transform' (copied below), which is used as an input parameter when loading the training and testing datasets from CIFAR10.

"transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((.5, .5, .5),(.5, .5, .5))])"

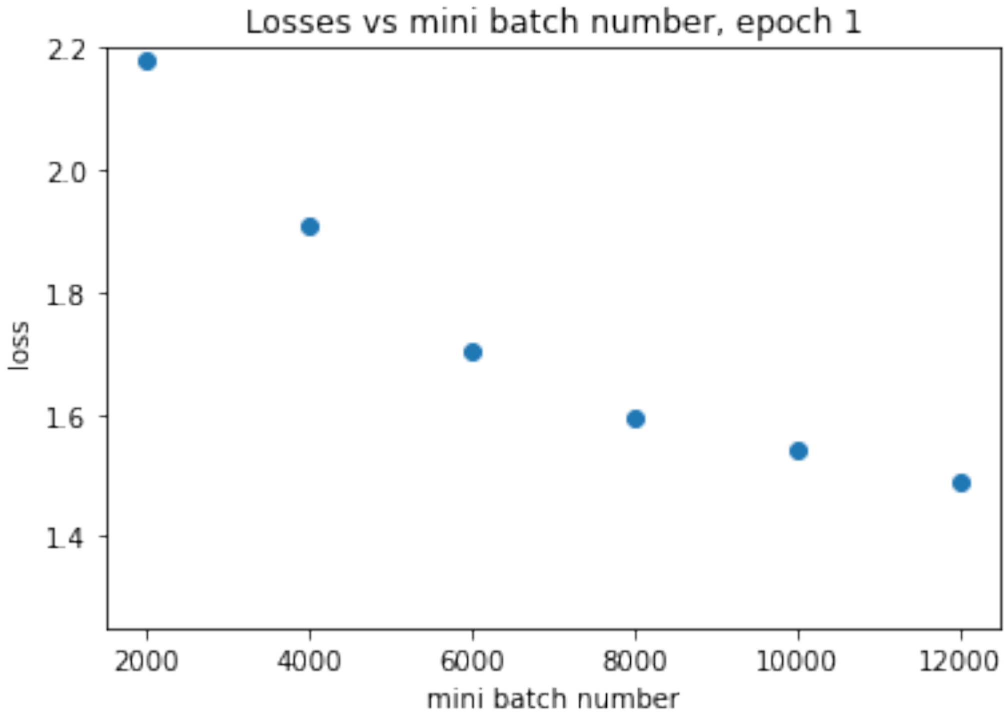
(iv)

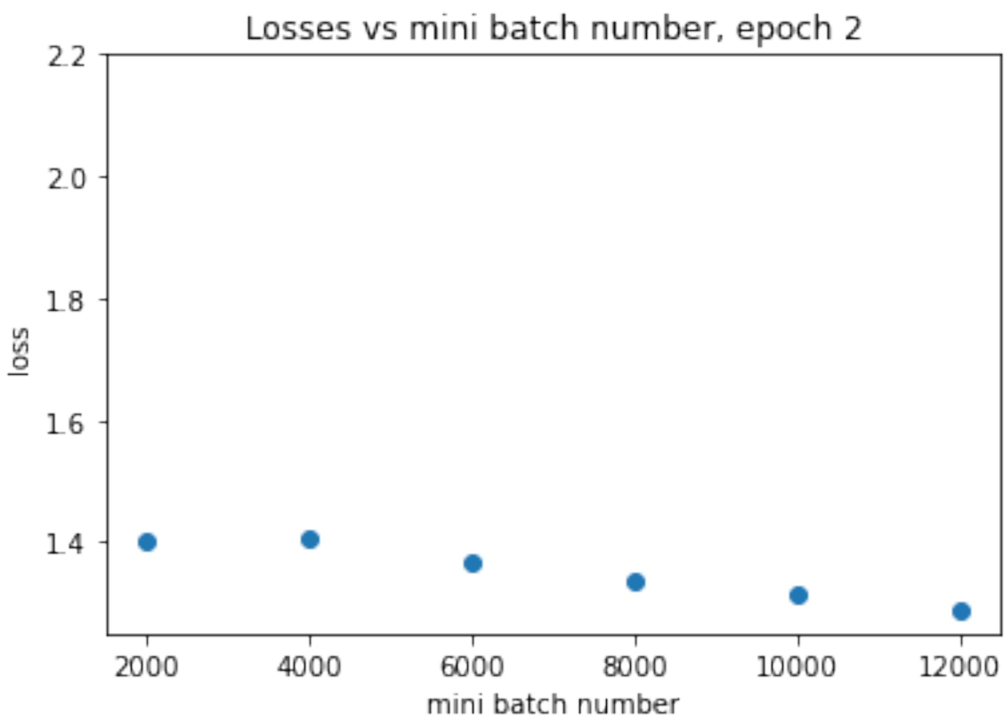
The losses are dropping! Can you plot out the training loss?

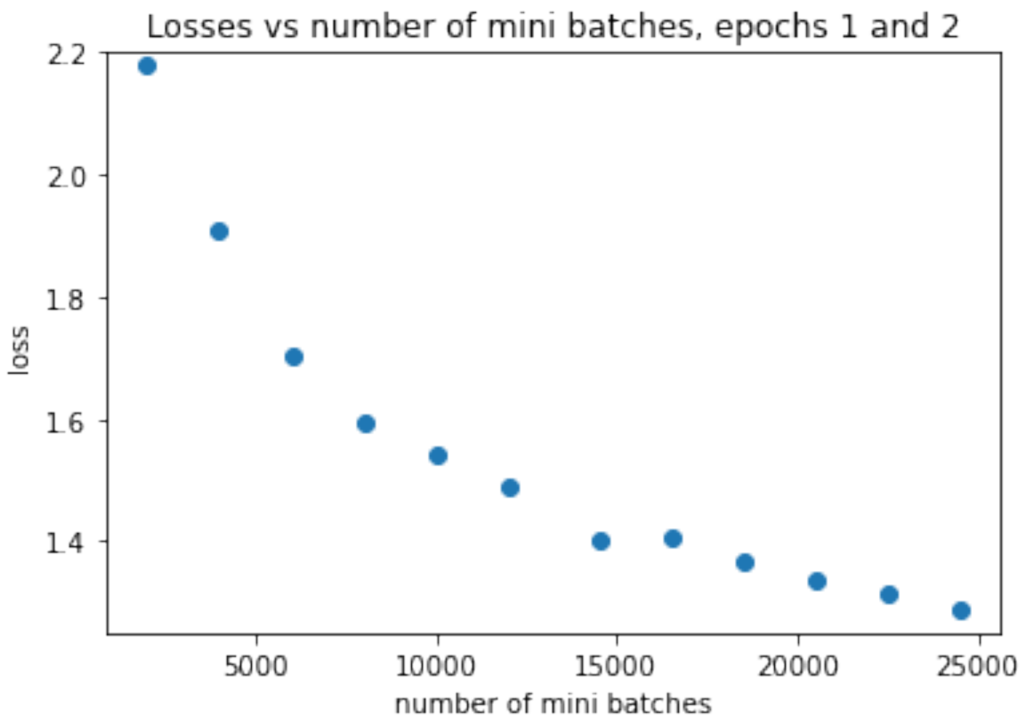
Yes, see plots below for epoch 1 and 2. Please note that training took hours so rather than rewriting the training code block to save the losses in a vector or list for plotting later, the vector was defined by hand from the printed out losses in the training block in order to save time and sanity. It can be observed that the loss decreses rapidly before starting to level off towards the end of the second epoch. It briefly increases at the beginning of the second epoch before decreasing again. This is not uncommon in training.

In [65]:

```
import numpy as np
import matplotlib.pyplot as plt

#epoch 1
losses1 = np.array([2.179,1.909,1.702,1.596,1.541,1.488])
#epoch 2
losses2 = np.array([1.400,1.408,1.368,1.338,1.314,1.287])
#mini-batch number
miniBatch = np.array([2000,4000,6000,8000,10000,12000])

fig=plt.figure(1)
plt.scatter(miniBatch, losses1)
plt.title('Losses vs mini batch number, epoch 1')
plt.xlabel('mini batch number')
plt.ylabel('loss')
plt.ylim([1.25,2.2])

fig=plt.figure(2)
plt.scatter(miniBatch, losses2)
plt.title('Losses vs mini batch number, epoch 2')
plt.xlabel('mini batch number')
plt.ylabel('loss')
plt.ylim([1.25,2.2])




fig=plt.figure(3)
lossesTotal = np.append(losses1, losses2)

miniBatchTotal = np.append(miniBatch, miniBatch+12500)
plt.scatter(miniBatchTotal, lossesTotal)
plt.title('Losses vs number of mini batches, epochs 1 and 2')
plt.xlabel('number of mini batches')
plt.ylabel('loss')
plt.ylim([1.25,2.2])

plt.show()
```


Losses vs mini batch number, epoch 1
2.2
2.0
1.8
1.6
1.4
loss
2000
4000
6000
8000
10000
12000
mini batch number


Losses vs mini batch number, epoch 2
2.2
2.0
1.8
1.6
1.4
loss
2000
4000
6000
8000
10000
12000
mini batch number



In [64]:

```
print(miniBatch+12500)
```

```
[14500 16500 18500 20500 22500 24500]
```

(v)

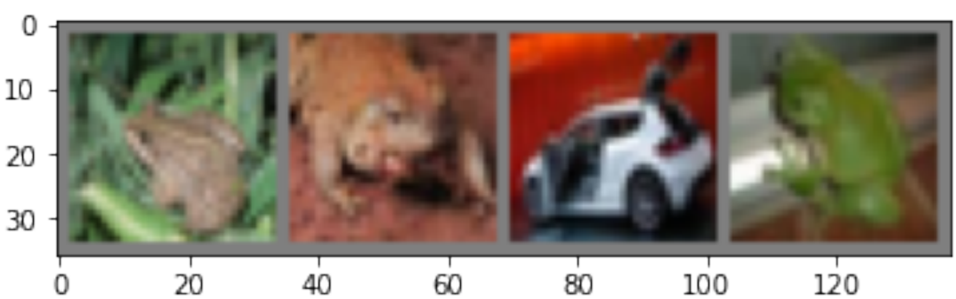
Now the network is done training. Can you check some successful cases and some failure cases (show some images classified by the network)?

Yes, see below, using code from the tutorial above. The network is not perfect but is much better than a random guess, showing that the network did learn something.

In [88]:

```
net = Net()
net.load_state_dict(torch.load(PATH))

dataiter = iter(testloader)
for i in range(0,10):
    images, labels = dataiter.next()

    # print images
    imshow(torchvision.utils.make_grid(images))
    print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))

    outputs = net(images)

    _, predicted = torch.max(outputs, 1)

    print('Predicted: ', ' '.join('%5s' % classes[predicted[j]] for j in range(4)))
```


```
GroundTruth:    cat  ship  ship plane
Predicted:   bird   car   car plane
```



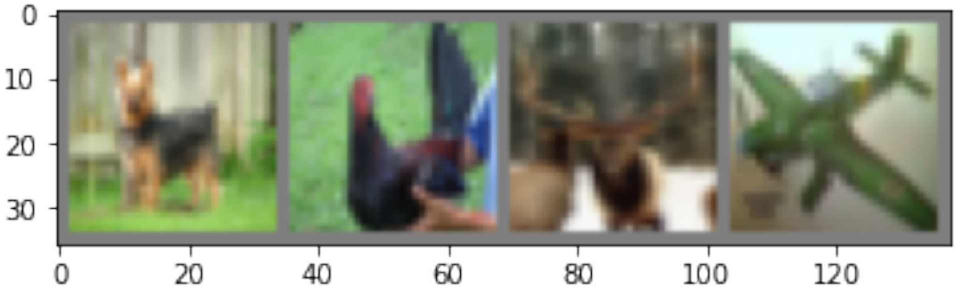

```
GroundTruth:   frog  frog   car  frog
Predicted:    cat  frog   cat  deer
```


```
GroundTruth:    cat   car plane truck
Predicted:    cat   car plane truck
```

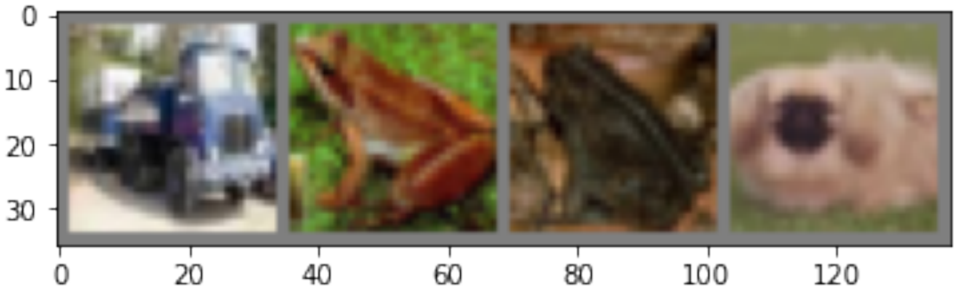

```
GroundTruth:    dog horse truck  ship
Predicted:    cat horse truck  frog
```


```
GroundTruth:    dog horse  ship  frog
Predicted:    cat   cat  ship  frog
```


```
GroundTruth:  horse plane  deer truck
Predicted:  horse plane plane truck
```




```
GroundTruth:    dog  bird  deer plane
Predicted:   deer  frog  deer  bird
```




```
GroundTruth:  truck  frog  frog   dog
Predicted:    car  frog   cat  bird
```


```
GroundTruth:   deer   dog truck  bird
Predicted:   deer   cat truck   cat
```


```
GroundTruth:   deer   car truck   dog
Predicted:  horse   car truck   dog
```

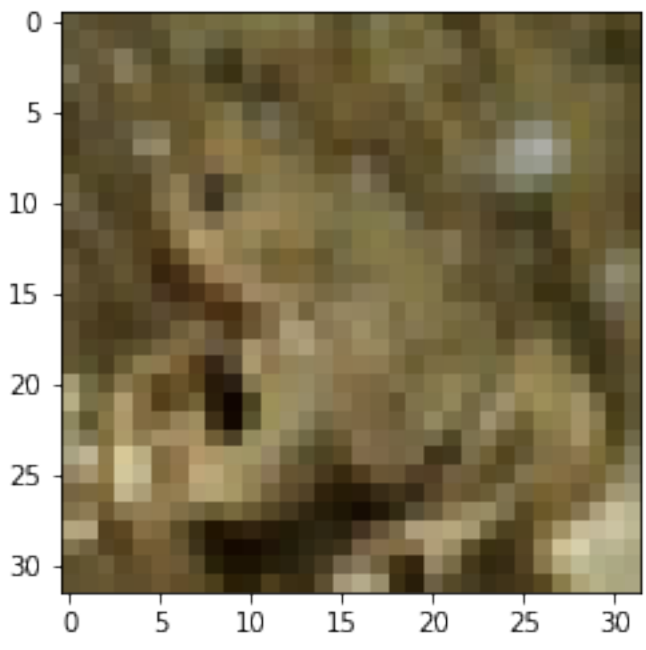
(vi)

Can you visualize the output of the 1st layer of CNN using one image from the training set?

In [183]:

```
for i, data in enumerate(trainloader, 0):
    # get the inputs; data is a list of [inputs, labels]
    inputs, labels = data
    image = inputs[0]
    label = labels[0]
print('Image to be used to visualize output of 1st layer of CNN'
)
imshow(image)
print(label)
```

```
Image to be used to visualize output of 1st layer of
CNN
```




```
tensor(6)
```

In [211]:

```
from scipy.signal import convolve
from scipy.ndimage import correlate
def convolve3D (image, kernal):
    #inputs both (x,x,3)
    layer1 = correlate(image[:,:,0], kernal[:,:,0], mode = 'wrap
')
    layer2 = correlate(image[:,:,1], kernal[:,:,1], mode = 'wrap
')
    layer3 = correlate(image[:,:,2], kernal[:,:,2], mode = 'wrap
')
    result = np.dstack([layer1, layer2, layer3])
    return result
```

In [212]:

```
weights = net.conv1.weight.data.numpy()
print(weights.shape)
weights.T.shape
print(weights.shape)
newWeights = (1/2) + weights/2

imageNP = np.transpose(image.numpy(),(1,2,0))
imageNP = (1/2) + imageNP/2

output = [0,0,0,0,0,0]

for i in range(0,6):
    filter = np.transpose(newWeights[i,...],(1,2,0))
    output[i] = convolve3D(imageNP, filter)
    output[i] = ((output[i]-np.amin(output[i]))/(np.amax(output[
i])-np.amin(output[i])))

plt.figure(figsize=(10,10))
plt.subplot(321)
plt.imshow(output[0])
plt.title('output ' + str(1) + ' for first layer of CNN')

plt.subplot(322)
plt.imshow(output[1])
plt.title('output ' + str(2) + ' for first layer of CNN')

plt.subplot(323)
```

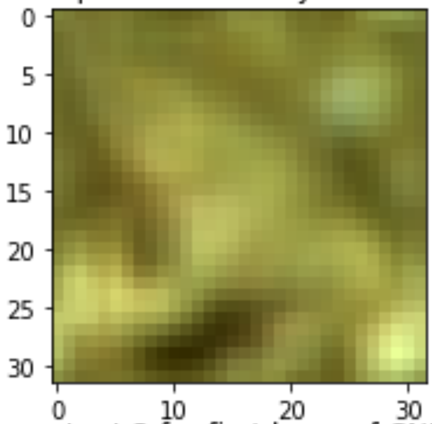
```python
plt.imshow(output[2])

plt.title('output ' + str(3) + ' for first layer of CNN')

plt.subplot(324)
plt.imshow(output[3])
plt.title('output ' + str(4) + ' for first layer of CNN')

plt.subplot(325)
plt.imshow(output[4])
plt.title('output ' + str(5) + ' for first layer of CNN')

plt.subplot(326)
plt.imshow(output[5])
plt.title('output ' + str(6) + ' for first layer of CNN')
```

```
(6, 3, 5, 5)
(6, 3, 5, 5)
```

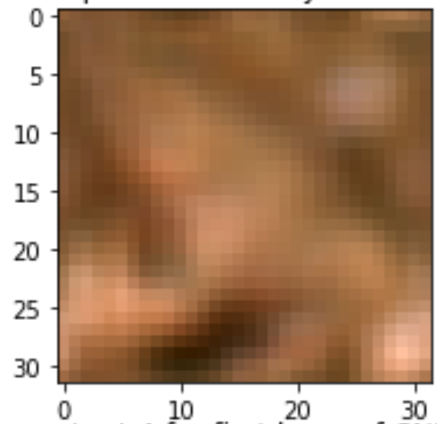
Out[212]:

```
Text(0.5, 1.0, 'output 6 for first layer of CNN')
```

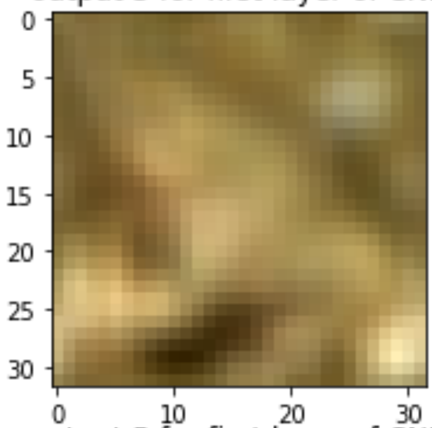
output 1 for first layer of CNN



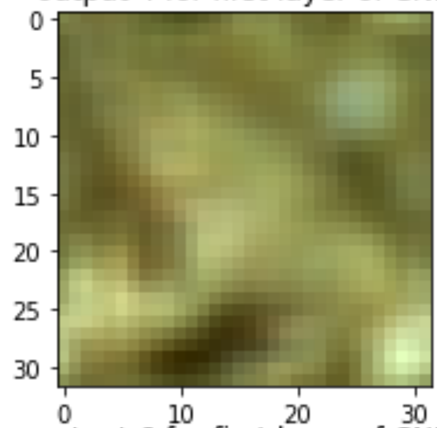
output 2 for first layer of CNN



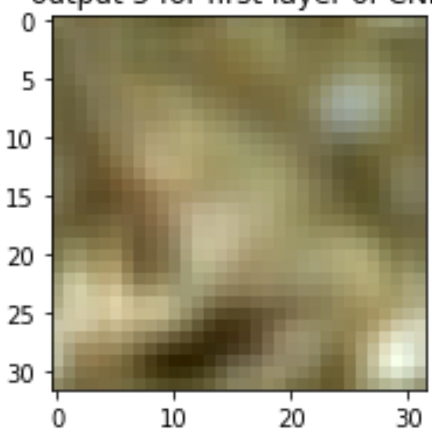
output 3 for first layer of CNN



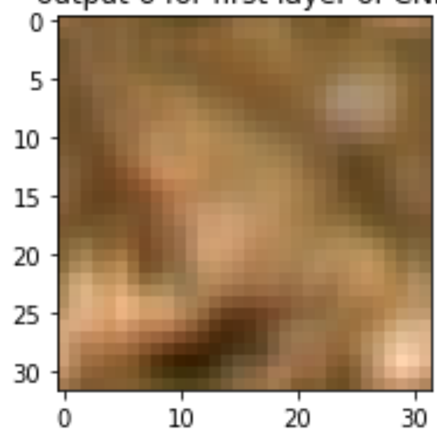
output 4 for first layer of CNN



output 5 for first layer of CNN



output 6 for first layer of CNN



In [ ]:

```
```