DIP HW6

Q1:

```
function result = gaborKernel2d( lambda, theta, phi, gamma, bandwidth)
%   LAMBDA -period of the cosine factor [in pixels]
%   SIGMA - standard deviation of the Gaussian factor [in pixels]
%   THETA - preferred orientation [in radians]
%   PHI   - phase offset [in radians] of the cosine factor
%   GAMMA - the x-axis and y-axis of the Gaussian elipse
%   BANDWIDTH - 50% spatial frequency bandwidth

ratio = (1/pi) * sqrt( (log(2)/2) ) * ( (2^bandwidth + 1) / (2^bandwidth -
1) );

% calcuate sigma
sigma = ratio * lambda;

% compute the size of the 2n+1 x 2n+1 matrix to be filled with the values of
a Gabor function
if (gamma <= 1 && gamma > 0)
    n = ceil(2.5*sigma/gamma);
else
    n = ceil(2.5*sigma);
end

[x,y] = meshgrid(-n:n);

% change direction of y-axis
y = -y;

xp =  x * cos(theta) + y * sin(theta);
yp = -x * sin(theta) + y * cos(theta);

% precompute coefficients gamma2=gamma*gamma, b=1/(2*sigma*sigma) and spacial
frequency
% f = 2*pi/lambda to prevent multiple evaluations
gamma2 = gamma*gamma;
b = 1 / (2*sigma*sigma);
a = b / pi;
f = 2*pi/lambda;

% filling (2n+1) x (2n+1) matrix result with the values of a 2D Gabor
function
result = a*exp(-b*(xp.*xp + gamma2*(yp.*yp))) .* cos(f*xp + phi);

end
```

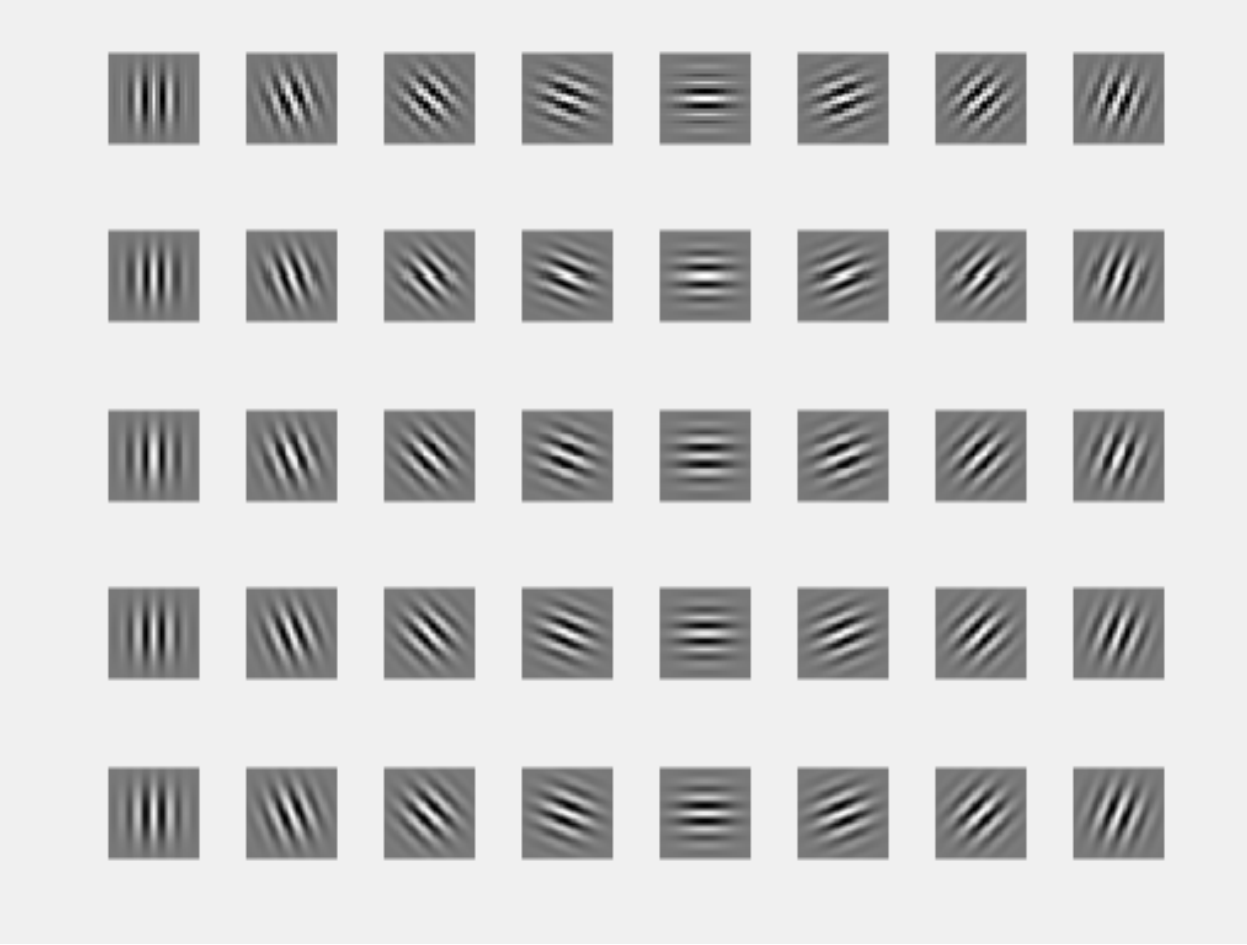
main function:

```
theta = [0 pi/8 2*pi/8 3*pi/8 4*pi/8 5*pi/8 6*pi/8 7*pi/8];
lambda = [4 6 8 10 12];
phi = 0;
gamma = 1;
bw = 0.5;
```

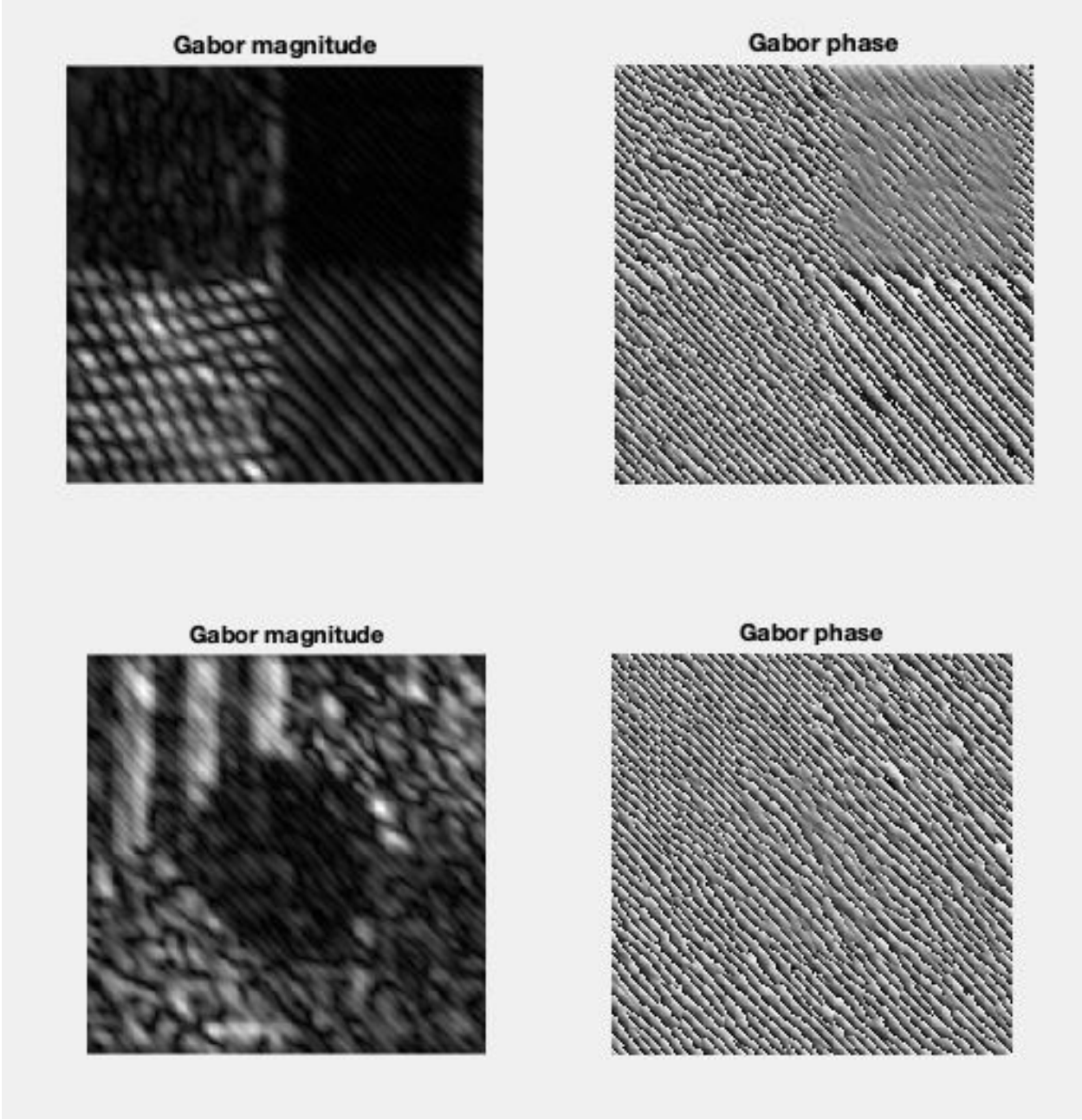
```
figure;
for i = 1:5
    for j = 1:8
        m=i+j;
        gaborFilter=gaborKernel2d(lambda(i), theta(j), phi, gamma, bw);

        subplot(5,8,(i-1)*8+j);
        %gaborAll(m,i,j)=real(gaborFilter);
        imshow(real(gaborFilter),[]);
    end
end

%imshow(real(gaborAll),[]);
```

Q2:

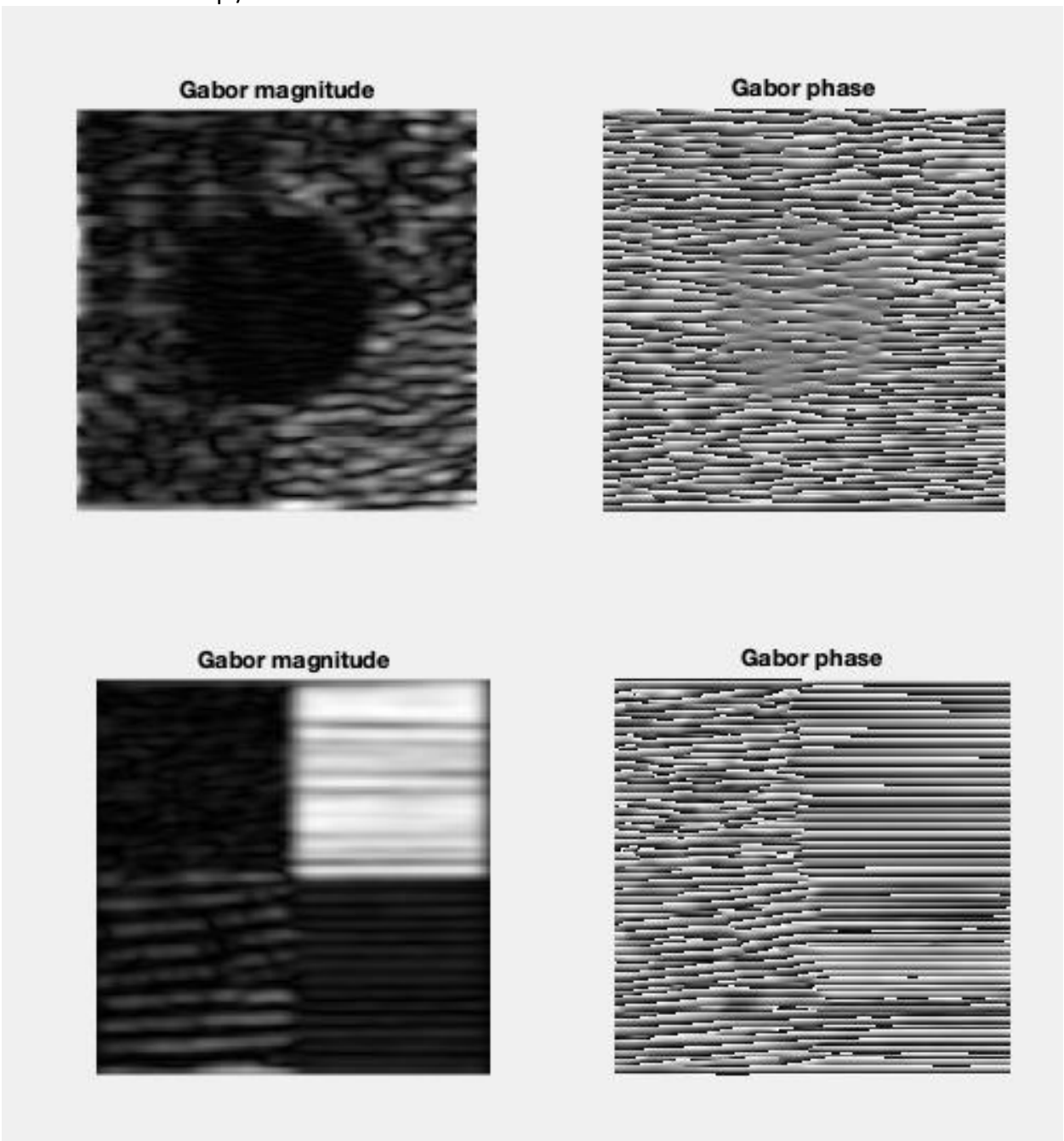
I know there is difference between my result and example(and I know the result will be same if I use build-in Matlab function: imgaborfilt). I just keep the result as it to find the reason. I guess it's the abs/real part matters.



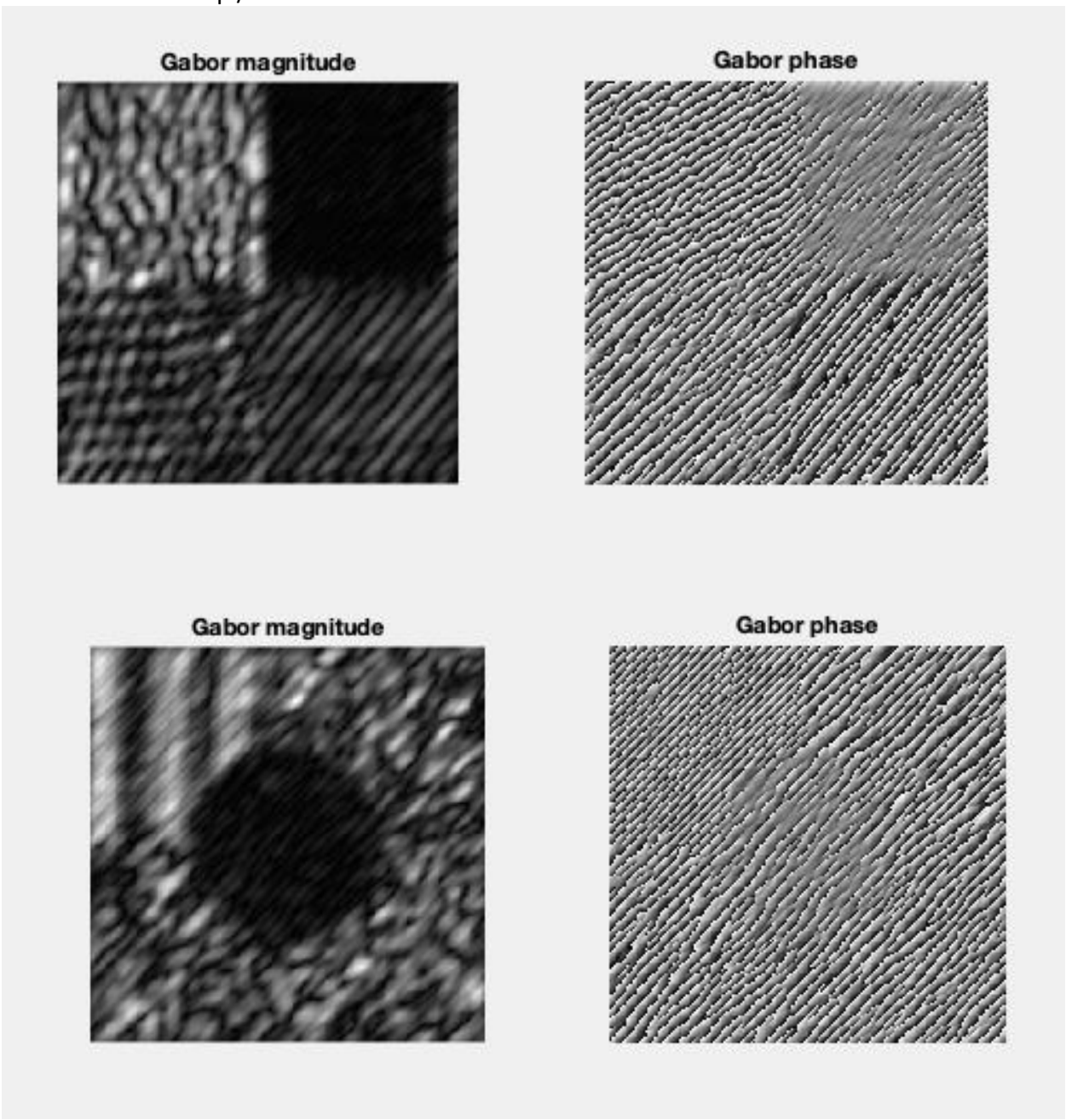
Q3:
If the orientation = pi/4



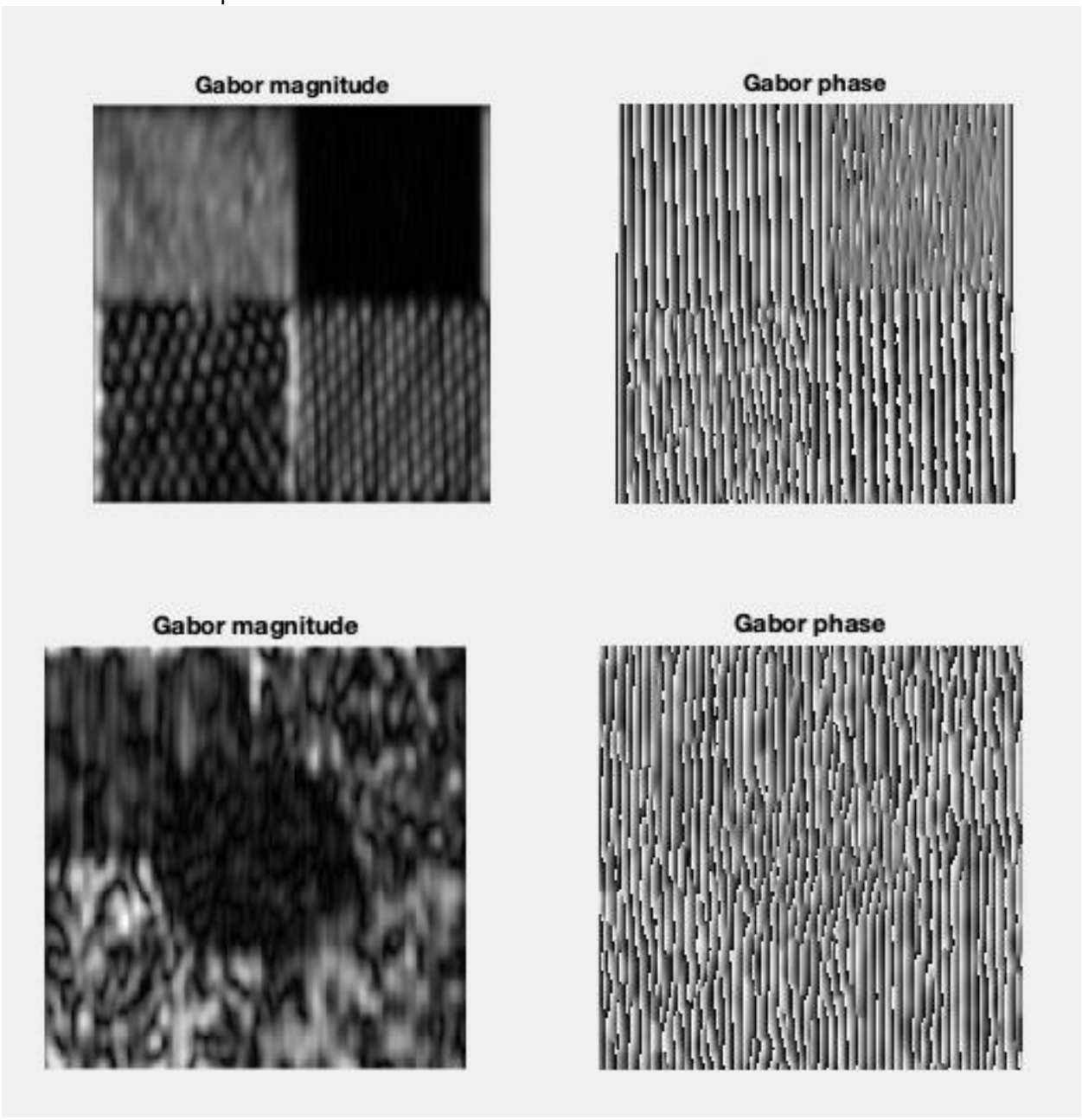
If the orientation = pi/2



If the orientation = pi/3



If the orientation = pi



Q4:
First step: use the Gabor find the texture.
Second step: use the k-means function to clarify the types.

I follow the tutorial of Matlab: https://www.mathworks.com/help/images/texture-segmentation-using-gabor-filters.html
And I change the k-means part and adjust the iteration times. The results are good so I don't change it(In fact I go to enjoy the Thanksgiving day : )

```
% Texture Segmentation Using Gabor Filters
% This example shows how to use texture segmentation to identify regions
based on their texture. The goal is to segment the dog from the bathroom
floor. The segmentation is visually obvious because of the difference in
texture between the regular, periodic pattern of the bathroom floor, and the
regular, smooth texture of the dog's fur.
% From experimentation, it is known that Gabor filters are a reasonable model
of simple cells in the Mammalian vision system. Because of this, Gabor
filters are thought to be a good model of how humans distinguish texture, and
are therefore a useful model to use when designing algorithms to recognize
texture. This example uses the basic approach described in (A. K. Jain and F.
Farrokhnia, "Unsupervised Texture Segmentation Using Gabor Filters",1991) to
perform texture segmentation.
% Read and display input image
% Read and display the input image. This example shrinks the image to make
the example run more quickly.
A = imread('brodatz4.png');
%A = imresize(A,0.25);
Agray = rgb2gray(A);
figure
imshow(A)

% Design Array of Gabor Filters
% Design an array of Gabor Filters which are tuned to different frequencies
and orientations. The set of frequencies and orientations is designed to
localize different, roughly orthogonal, subsets of frequency and orientation
information in the input image. Regularly sample orientations between [0,150]
degrees in steps of 30 degrees. Sample wavelength in increasing powers of two
starting from 4/sqrt(2) up to the hypotenuse length of the input image. These
combinations of frequency and orientation are taken from [Jain,1991] cited in
the introduction.
imageSize = size(A);
numRows = imageSize(1);
numCols = imageSize(2);

wavelengthMin = 4/sqrt(2);
wavelengthMax = hypot(numRows,numCols);
n = floor(log2(wavelengthMax/wavelengthMin));
wavelength = 2.^(0:(n-2)) * wavelengthMin;

deltaTheta = 45;
orientation = 0:deltaTheta:(180-deltaTheta);
```

```
g = gabor(wavelength,orientation);

%Extract Gabor magnitude features from source image. When working with Gabor
filters, it is common to work with the magnitude response of each filter.
Gabor magnitude response is also sometimes referred to as "Gabor Energy".
Each MxN Gabor magnitude output image in gabormag(:,:,ind) is the output of
the corresponding Gabor filter g(ind).
gabormag = imgaborfilt(Agray,g);

% Post-process the Gabor Magnitude Images into Gabor Features.
% To use Gabor magnitude responses as features for use in classification,
some post-processing is required. This post processing includes Gaussian
smoothing, adding additional spatial information to the feature set,
reshaping our feature set to the form expected by the pca and kmeans
functions, and normalizing the feature information to a common variance and
mean.
% Each Gabor magnitude image contains some local variations, even within well
segmented regions of constant texture. These local variations will throw off
the segmentation. We can compensate for these variations using simple
Gaussian low-pass filtering to smooth the Gabor magnitude information. We
choose a sigma that is matched to the Gabor filter that extracted each
feature. We introduce a smoothing term K that controls how much smoothing is
applied to the Gabor magnitude responses.
for i = 1:length(g)
    sigma = 0.5*g(i).Wavelength;
    K = 3;
    gabormag(:,:,i) = imgaussfilt(gabormag(:,:,i),K*sigma);
end

%When constructing Gabor feature sets for classification, it is useful to add
a map of spatial location information in both X and Y. This additional
information allows the classifier to prefer groupings which are close
together spatially.
X = 1:numCols;
Y = 1:numRows;
[X,Y] = meshgrid(X,Y);
featureSet = cat(3,gabormag,X);
featureSet = cat(3,featureSet,Y);

%Reshape data into a matrix X of the form expected by the kmeans function.
Each pixel in the image grid is a separate datapoint, and each plane in the
variable featureSet is a separate feature. In this example, there is a
separate feature for each filter in the Gabor filter bank, plus two
additional features from the spatial information that was added in the
previous step. In total, there are 24 Gabor features and 2 spatial features
for each pixel in the input image.
numPoints = numRows*numCols;
X = reshape(featureSet,numRows*numCols,[]);

%Normalize the features to be zero mean, unit variance.
X = bsxfun(@minus, X, mean(X));
X = bsxfun(@rdivide,X,std(X));
```

```
%Visualize the feature set. To get a sense of what the Gabor magnitude
features look like, Principal Component Analysis can be used to move from a
26-D representation of each pixel in the input image into a 1-D intensity
value for each pixel.
coeff = pca(X);
feature2DImage = reshape(X*coeff(:,1),numRows,numCols);
figure
imshow(feature2DImage,[])
%It is apparent in this visualization that there is sufficient variance in
the Gabor feature information to obtain a good segmentation for this image.
The dog is very dark compared to the floor because of the texture differences
between the dog and the floor.

%Classify Gabor Texture Features using kmeans
%Repeat k-means clustering five times to avoid local minima when searching
for means that minimize objective function. The only prior information
assumed in this example is how many distinct regions of texture are present
in the image being segmented. There are two distinct regions in this case.
This part of the example requires the Statistics and Machine Learning
Toolbox?.
L = kmeans(X,4,'Replicates',3);

%Visualize segmentation using label2rgb.
L = reshape(L,[numRows numCols]);
figure
imshow(label2rgb(L))

%Visualize the segmented image using imshowpair. Examine the foreground and
background images that result from the mask BW that is associated with the
label matrix L.
Aseg1 = zeros(size(A),'like',A);
Aseg2 = zeros(size(A),'like',A);
BW = L == 2;
BW = repmat(BW,[1 1 3]);
Aseg1(BW) = A(BW);
Aseg2(~BW) = A(~BW);
figure
imshowpair(Aseg1,Aseg2,'montage');
%Copyright 2015 The MathWorks, Inc.
```

Where I change:

```
%Classify Gabor Texture Features using kmeans
%Repeat k-means clustering five times to avoid local minima when searching
for means that minimize objective function. The only prior information
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in the image being segmented. There are two distinct regions in this case.
This part of the example requires the Statistics and Machine Learning
Toolbox?.
L = kmeans(X,4,'Replicates',3);
```

Results:

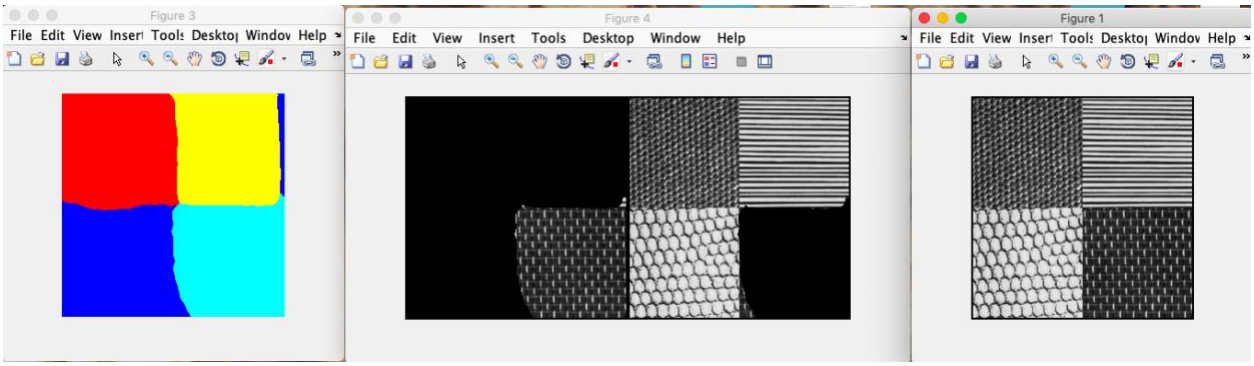
Figure 3
Figure 4
Figure 1
File Edit View Insert Tools Desktop Window Help

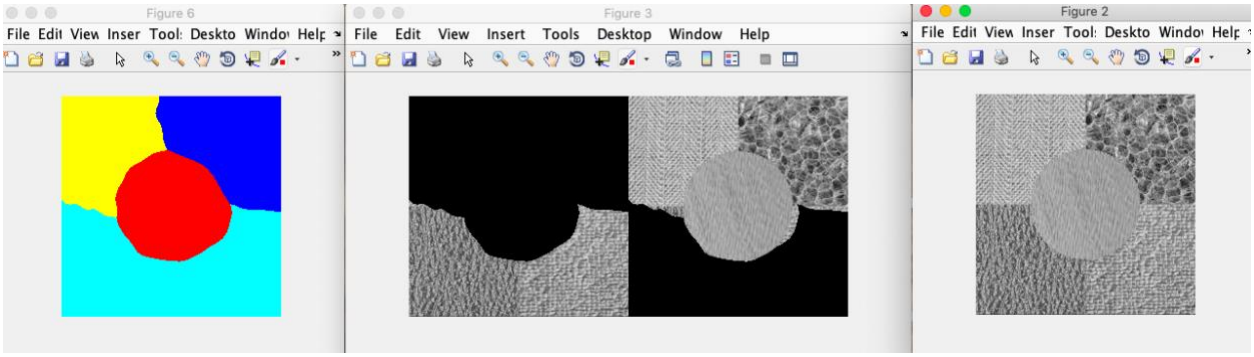
Figure 6
Figure 3
Figure 2
File Edit View Insert Tools Desktop Window Help