mmn_11_computer_vision

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1 MMN-11

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1.1 Preparatory Setup

1.1.1 Library Imports

```
In [2]: import numpy as np
        import cv2
        import matplotlib.pyplot as plt
        %matplotlib inline
```

1.2 Preparatory Setup

1.2.1 PyPlot Defaults Configuration

```
In [3]: plt.rcParams['figure.figsize'] = [14,8]
        plt.rcParams['figure.frameon'] = False
        plt.rcParams['figure.edgecolor'] = 'none'
        plt.rcParams['figure.facecolor'] = 'none'
        plt.rcParams['ytick.left'] = False
        plt.rcParams['ytick.right'] = False
        plt.rcParams['xtick.bottom'] = False
        plt.rcParams['xtick.top'] = False
        plt.rcParams['ytick.labelleft'] = False
        plt.rcParams['ytick.labelright'] = False
        plt.rcParams['xtick.labelbottom'] = False
        plt.rcParams['xtick.labeltop'] = False
        plt.rcParams['axes.grid'] = False
        plt.rcParams['image.interpolation'] = 'bilinear'
```

1.3 Question 1

```
In [325]: img = cv2.imread('spock.jpg', cv2.IMREAD_COLOR)[...,::-1]  # converted to rgb on the
          plt.imshow(img)

Out[325]: <matplotlib.image.AxesImage at 0x11cc22d30>
```

In [326]:
```
# convert to grayscale monochrome since that's the input format for the algorithms b
gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
plt.imshow(gray, cmap='gray')
```

Out[326]:
```
<matplotlib.image.AxesImage at 0x11cd195c0>
```

1.3.1 Canny Edge Detector

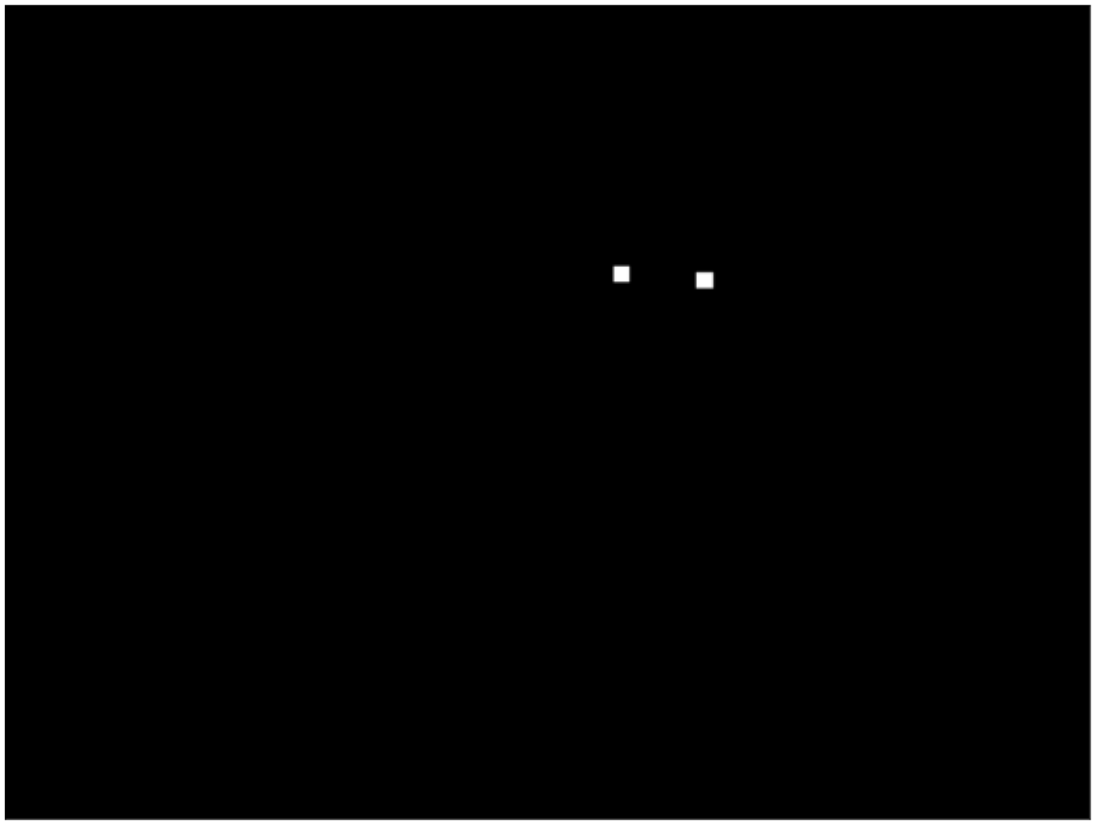
```
In [327]: edges = cv2.Canny(gray, 89, 144)
          plt.imshow(edges, cmap='gray')
```

```
Out[327]: <matplotlib.image.AxesImage at 0x119579780>
```

1.3.2 Harris Corner Detection

In [328]:
```
##### perform corner detection
corners = cv2.cornerHarris(gray,blockSize=2,ksize=3,k=0.08)

# discard detection values below threshold
# rationale: large positive detection values indicate corners
DETECTION_THRESHOLD = 1.0e-4
corners = np.where(corners>1.0e-4,255,0)


# discard sparse detections, and group together dense detection regions
# rationale: the eye corner areas are apparently dense with various corners
corners = cv2.medianBlur(corners.astype(np.uint8), 3)

# dilate detections for a clearer visualization
corners = cv2.dilate(corners, kernel=np.ones((13,13)), iterations=1)

# visualize detection map
plt.imshow(corners, cmap='gray')
```

Out[328]: <matplotlib.image.AxesImage at 0x11c803320>



In [329]:
```
# expand the monochrome image to rgb by duplicating the gray channel
corners_overlay = np.repeat(gray[:,:,None],repeats=3,axis=2)

# mark detection points with blue overlay
corners_overlay[...,2] = np.maximum(corners_overlay[...,2], corners)

# visualize grayscale image with blue overlay detection marks
plt.imshow(corners_overlay)
```

Out[329]: <matplotlib.image.AxesImage at 0x11931e048>

Sadly, pointed ear detections are not as easy to isolate :)

1.3.3 Scale Invariant Feature Transform (SIFT)

```
In [330]: # extract corner point coordinates by finding centroids of connected components
          eye_corner_coordinates = cv2.connectedComponentsWithStats(corners)[3][1:,:]

          # convert coordinates to Keypoint type
          eye_corner_keypoints = [cv2.KeyPoint(crd[0], crd[1], 13) for crd in eye_corner_coordi

          # compute SIFT descriptors from corner keypoints
          sift = cv2.xfeatures2d.SIFT_create()
          eye_corner_descriptors = [sift.compute(gray,[kp])[1] for kp in eye_corner_keypoints]

          print(eye_corner_descriptors)
```

```
[array([[  5.,  83.,  90.,   6.,   7.,  44.,  22.,   2.,   7.,
        113., 113.,   3.,   4.,  16.,   5.,   2.,  13., 107.,
         51.,   6.,   8.,   2.,   3.,   4.,  13.,  42.,  25.,
         12.,  10.,   5.,   6.,   3.,   8.,  13., 111.,  33.,
          9.,  74.,  81.,  48.,  14.,  75.,  77.,  27.,  17.,
         75., 113.,  61.,  22., 113.,  95.,   3.,   3.,  17.,
```

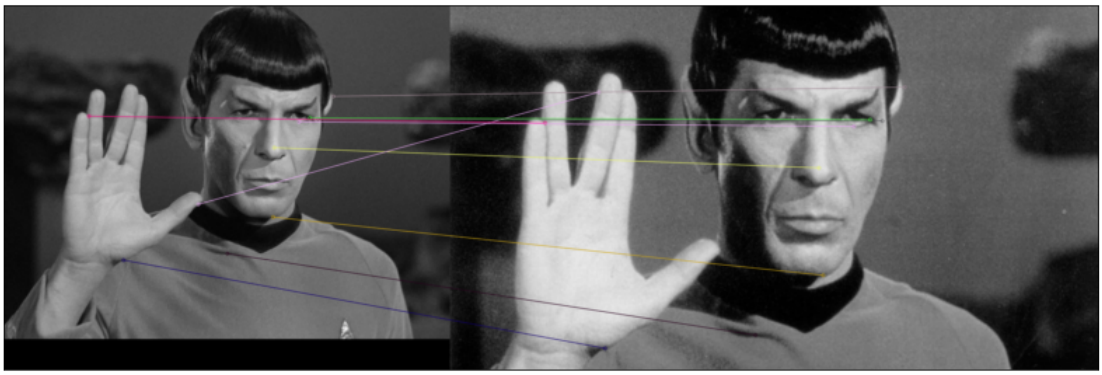
```
 74.,   17.,   86.,   54.,   37.,    9.,    8.,    5.,    6.,
 31.,    9.,    4.,    4.,    3.,    1.,   33.,  113.,   44.,
  9.,    5.,   12.,   19.,   15.,   54.,  113.,   36.,   43.,
  6.,    5.,   19.,   40.,   81.,   59.,   30.,  113.,    4.,
  0.,    2.,   18.,    7.,    4.,   76.,    4.,    4.,    3.,
  4.,    3.,    9.,   14.,    6.,    1.,    3.,   10.,   62.,
 24.,    7.,    4.,    3.,   66.,    5.,    2.,   74.,   40.,
 12.,    1.,   14.,  113.,    8.,    0.,    2.,   13.,    2.,
  0.,   28.]], dtype=float32), array([[  15.,   26.,   29.,   22.,    8.,    4.,    4
 14.,   97.,   44.,    4.,    1.,    4.,    4.,    4.,    7.,
112.,   85.,    3.,    2.,    5.,    6.,    5.,    4.,  112.,
 57.,    7.,    3.,   13.,   28.,   54.,    7.,    8.,   23.,
 74.,   24.,   13.,   32.,    1.,    3.,  112.,   96.,   70.,
 57.,   97.,   39.,   10.,   38.,  112.,   76.,   10.,  112.,
112.,   52.,   19.,   95.,  101.,   15.,    3.,   33.,   88.,
 72.,   50.,    2.,    0.,    3.,   64.,   18.,   10.,   31.,
 10.,    3.,    1.,    3.,   35.,   70.,  102.,   35.,    5.,
 13.,   17.,    8.,    9.,   98.,  112.,   33.,   11.,   27.,
 22.,    8.,    8.,   75.,  112.,   30.,   37.,    5.,    0.,
  3.,   47.,    6.,    1.,    8.,   20.,   16.,    1.,    1.,
 21.,   20.,    5.,    4.,    9.,    4.,    2.,    1.,    5.,
 16.,   21.,    9.,    3.,    2.,    2.,    3.,    3.,    7.,
 21.,    9.]], dtype=float32)]
```

1.3.4 SIFT Pattern Matching

In [331]:
```
# load and visualize images
img1 = cv2.imread('spock.jpg', cv2.IMREAD_GRAYSCALE)
img2 = cv2.imread('spock2.jpg', cv2.IMREAD_GRAYSCALE)
ax1, ax2 = plt.subplots(1,2)[1]
ax1.imshow(img1, cmap='gray'); ax2.imshow(img2, cmap='gray')
```

Out[331]:
```
<matplotlib.image.AxesImage at 0x11d58e9e8>
```

```
In [332]: # detect keypoints and compute descriptors
          kp1, des1 = sift.detectAndCompute(img1, None)
          kp2, des2 = sift.detectAndCompute(img2, None)

In [333]: # compute descriptor pattern matches
          brute_force_matcher = cv2.BFMatcher(crossCheck=True)
          matches = brute_force_matcher.match(des1, des2)
          # sort matches by way of matcher default distance function (l2 norm)
          matches = sorted(matches, key = lambda x:x.distance)

In [335]: # visualize top 10 matches
          matches_img = cv2.drawMatches(img1,kp1,img2,kp2,matches[:10],None, flags=2)
          plt.imshow(matches_img)

Out[335]: <matplotlib.image.AxesImage at 0x11cbe2c18>
```

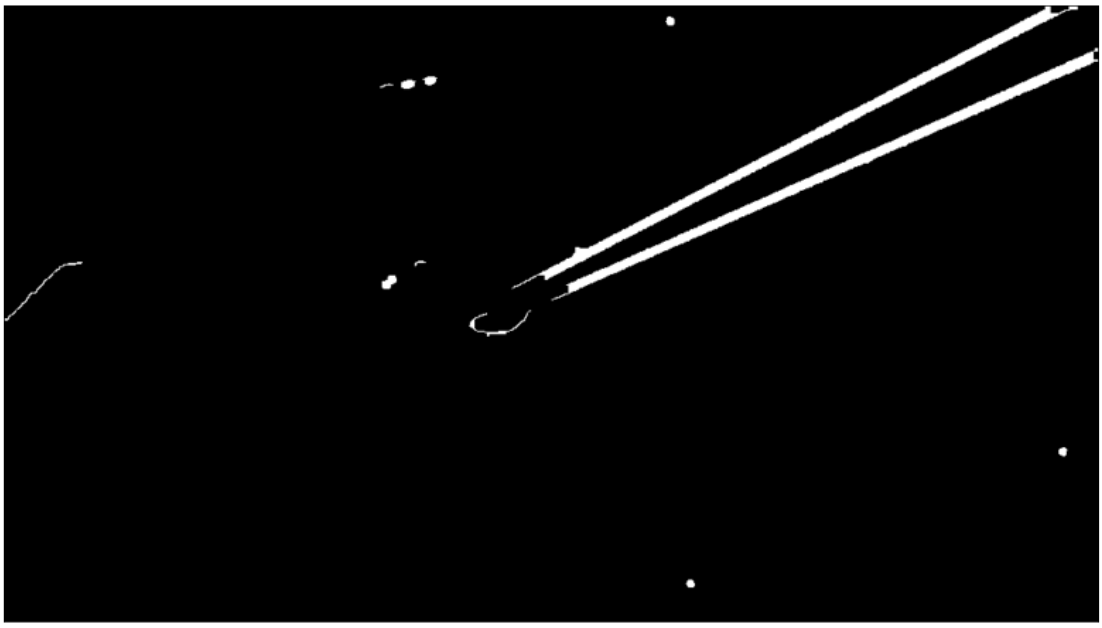


1.3.5 Hough Line Transform

```
In [15]: # load as BGR, convert to RGB, convert to grayscale, showcase
         phasers = cv2.imread('enterprise_phasers.jpg', cv2.IMREAD_COLOR)[...,::-1]
         phasers_gray = cv2.cvtColor(phasers, cv2.COLOR_RGB2GRAY)
         ax1, ax2 = plt.subplots(2,1)[1]
         ax1.imshow(phasers); ax2.imshow(phasers_gray, cmap='gray')

Out[15]: <matplotlib.image.AxesImage at 0x1133628d0>
```

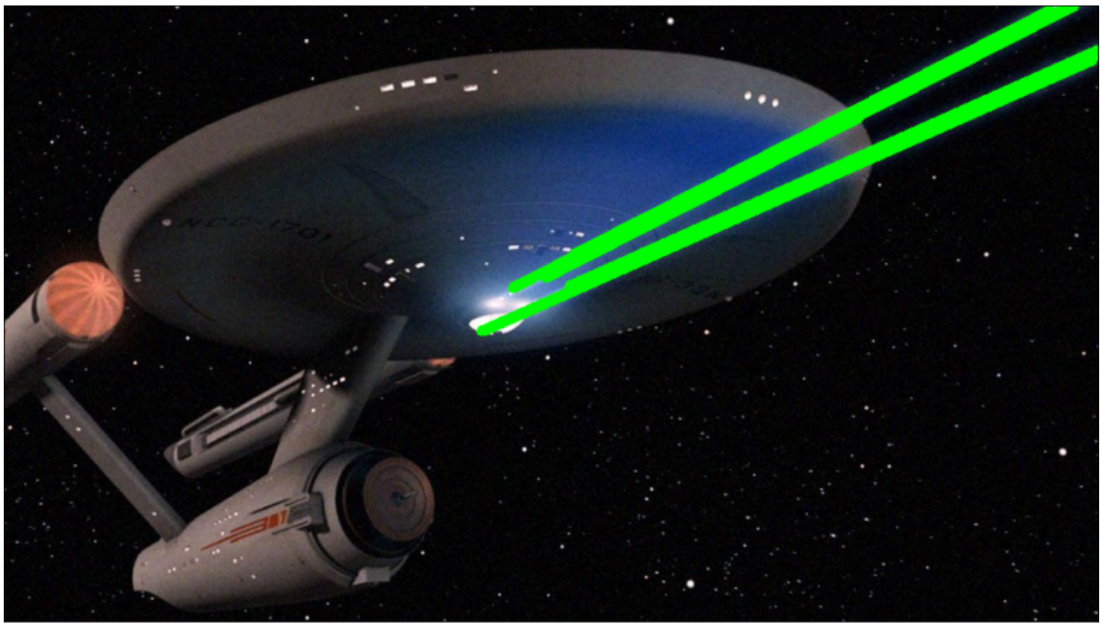
In [16]:
```
# isolate phaser rays
phaser_blur = cv2.blur(phasers_gray, (7,7))
phaser_edges = cv2.Canny(phaser_blur,128,256)
phaser_edges = cv2.morphologyEx(phaser_edges, cv2.MORPH_CLOSE, np.ones((7,7)))
plt.imshow(phaser_edges, cmap='gray')
```

Out[16]:
```
<matplotlib.image.AxesImage at 0x112e14588>
```



In [17]:
```
# find diagonal line terminal point coordinates
lines = cv2.HoughLinesP(phaser_edges, rho=1, theta=1.5*np.pi/180, threshold=256,
                        minLineLength=128, maxLineGap=64)

# draw found lines on image
phaser_lines = np.copy(phasers)
for line in lines:
    x1,y1,x2,y2 = line[0]
    cv2.line(phaser_lines,(x1,y1),(x2,y2),(0,255,0),7)

    # visualize result
plt.imshow(phaser_lines)
```

Out[17]:
```
<matplotlib.image.AxesImage at 0x112dc1a20>
```



1.4 Question 2

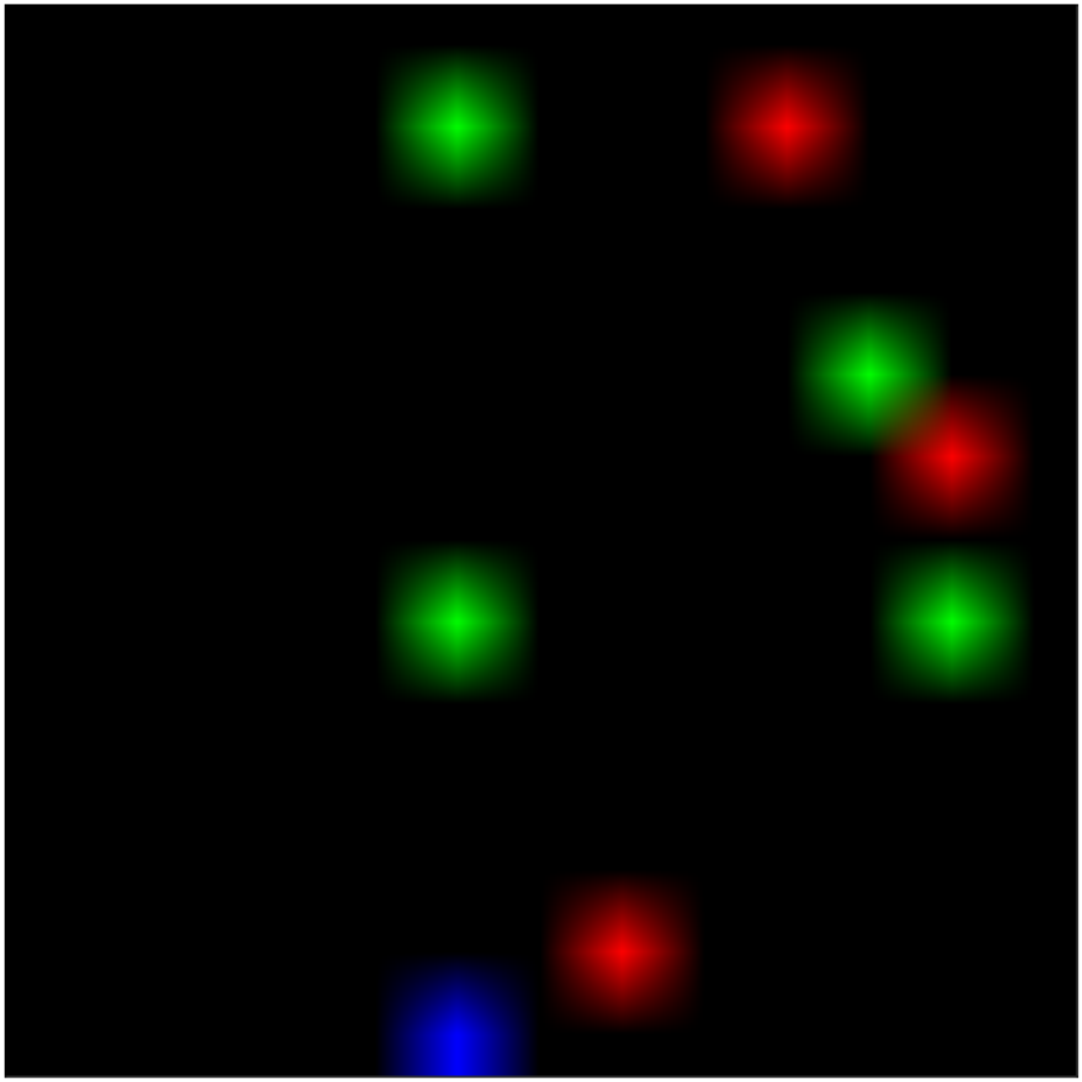
1.4.1 K-Means Clustering

We'll cluster 8 random points (without replacement) from the range [1,12] into 3 different groups.

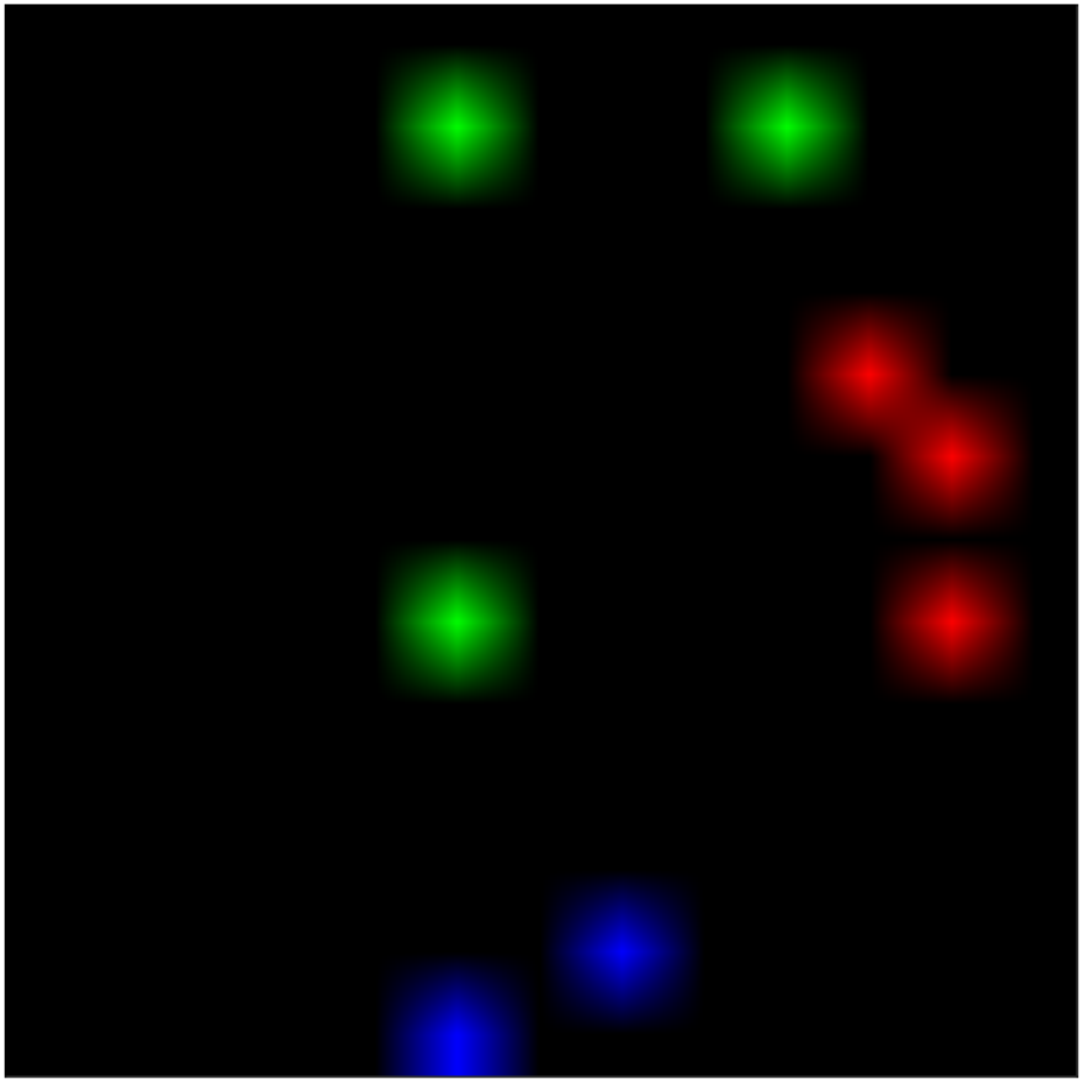
```
In [18]: # prints some data, plots cluster assignments
         def plot_kmeans_step(pts, lbls, i, cntrs):
             plt.figure()
             plot = np.zeros((13,13,3),np.uint8)
             colors = np.where(lbls==0, (255,0,0), lbls)
             colors = np.where(lbls==1, (0,255,0), colors)
             colors = np.where(lbls==2, (0,0,255), colors)
             pts_y, pts_x = pts.astype(np.uint8).T
             plot[pts_y, pts_x] = colors
             plt.imshow(plot)
             plt.suptitle('iteration='+str(i)+', centers=\n'+str(cntrs))
```

```
In [17]: # select random 2d coordinates from valid range
         pts = np.random.permutation(np.mgrid[1:13, 1:13].reshape(2, -1).T)[:8].astype(np.floa
         #  randomly set initial kmeans cluster assignments
         lbls = np.random.choice(3,(8,1)).astype(np.int32)
         # plot initial assignment
         plot_kmeans_step(pts, lbls, 0, 'not computed yet')

         # previous iteration's cluster centers
         old_cntrs=None
```

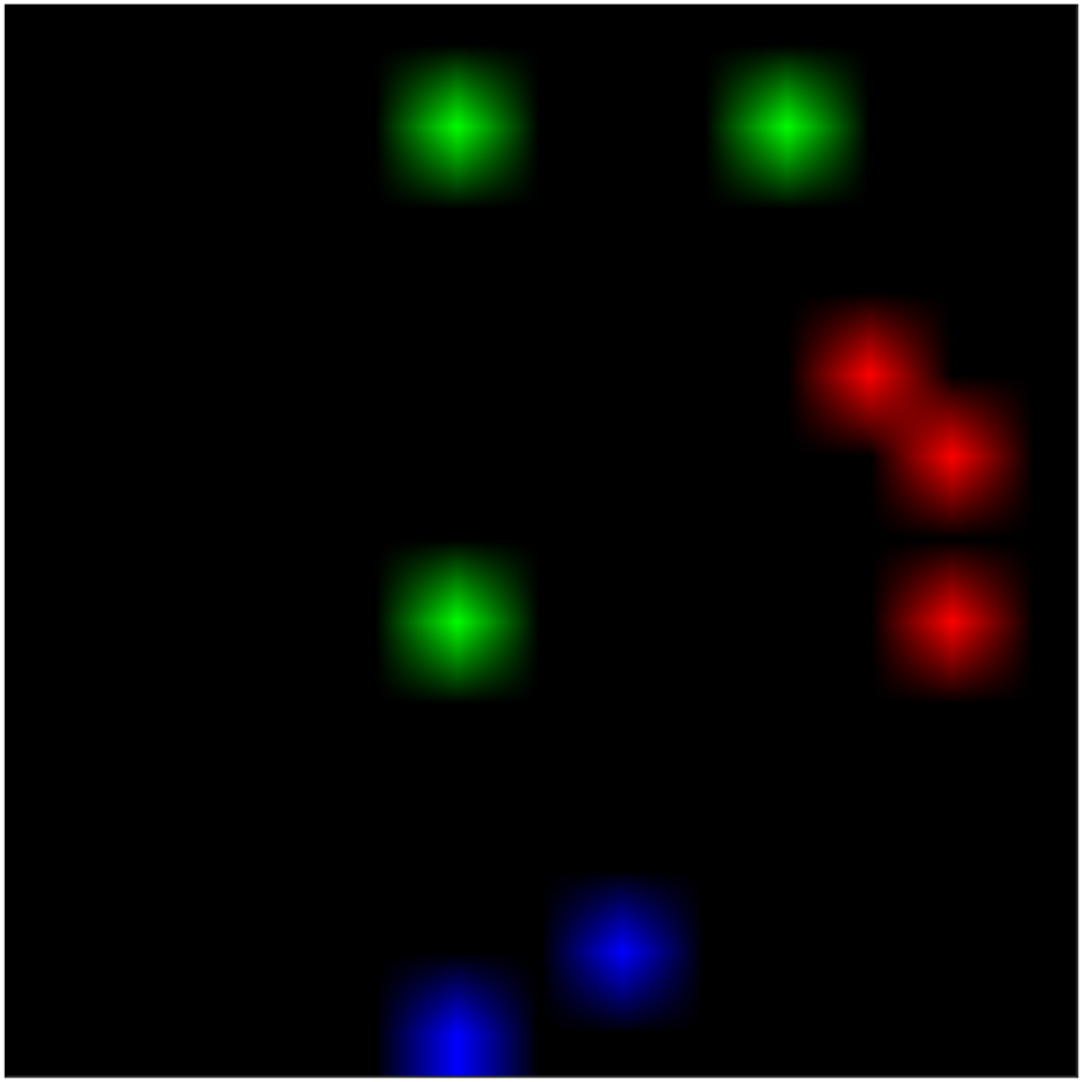
```
for i in range(100):
    # run kmeans for 1 step
    ret,lbls,cntrs = cv2.kmeans(pts,
                                K=3,
                                bestLabels=lbls,
                                criteria=(cv2.TERM_CRITERIA_MAX_ITER, 1, 1.0),
                                attempts=1,
                                flags=cv2.KMEANS_USE_INITIAL_LABELS)
    # print some data, plot current cluster assignments
    plot_kmeans_step(pts, lbls, i, cntrs)
    # terminate loop when centers didn't change from last iteration
    if np.array_equal(cntrs, old_cntrs):
        break;
    old_cntrs=cntrs
```


iteration=0, centers=not computed yet

iteration=0, centers=[[5.33333349 10.66666698]
 [3.   6.33333349]
 [11.5   6.   ]]



iteration=1, centers=[[5.33333349 10.66666698]
[3. 6.33333349]
[11.5 6.]]



1.5 Question 3

1.5.1 Least Squares Polynomial Fitting

Overview We'll fit a parabolic curve to a set of 2d points using the least squares method. The least squares method works by finding a curve such that the sum of the squared errors between the given coordinates and the curve is miniminal.

Math The error is defined as

$$E = \Sigma_{i=0}^{n}(f(x_i) - y_i)^2$$

Where $f(x)$ is our parabola fitting function and x_i, y_i are the input coordinates.

We'll minimize the error by computing the vandermonde matrix

$$\mathbf{y} = \mathbf{Xa}$$

Where $\mathbf{y}$ are the y coordinate column vector, $\mathbf{X}$ is the x coordinate polynomial power matrix, and $\mathbf{a}$ is the sought coefficient column vector.

Note: see wolfram least squares polynomial fitting

```
In [299]: # the specificed input coordinates
          pts = np.array(((1,3.96), (4,27.96), (3,15.15), (5,45.8), (2,7.07), (6,69.4)))
          pts
```

```
Out[299]: array([[  1.  ,   3.96],
                 [  4.  ,  27.96],
                 [  3.  ,  15.15],
                 [  5.  ,  45.8 ],
                 [  2.  ,   7.07],
                 [  6.  ,  69.4 ]])
```

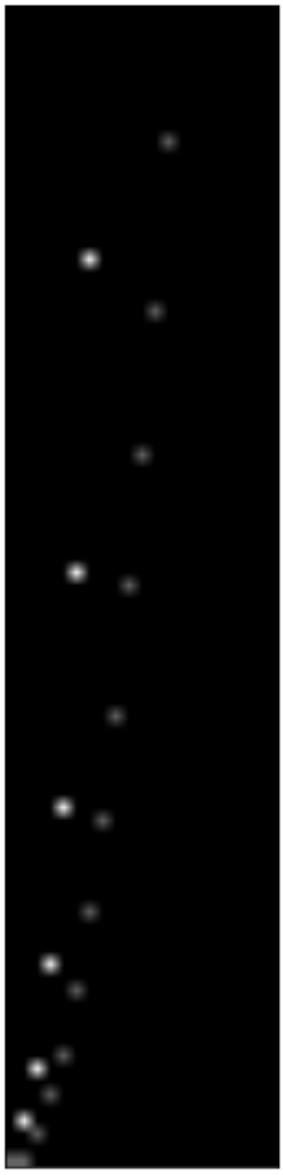
```
In [109]: # calculate the x coordinate powers matrix
          pts_x_pow = np.stack(((pts[:,0]**2).T, pts[:,0].T, np.ones(pts.shape[0]).T)).T
          # solve the linear equation
          dst = cv2.solve(pts[:,1],x, flags=cv2.DECOMP_NORMAL)[1]
```

Note: see decomposition types

```
In [110]: # set curve x values
          curve_x = np.arange(13)
          # calculate curve y values
          curve_x_pow = np.stack(((curve_x**2).T, curve_x.T, np.ones(curve_x.shape[0]).T)).T
          curve_y = np.matmul(curve_x_pow,dst.T).ravel().astype(np.uint8)
```

```
In [111]: # plot input points and points on calculated curve
          pts_x, pts_y = pts.astype(np.uint8).T
          plot = np.zeros((89,21), np.uint8)
          plot[pts_y, pts_x] = 255; plot[curve_y, curve_x] = 100
          plt.imshow(plot[::-1,:], cmap='gray')
```

```
Out[111]: <matplotlib.image.AxesImage at 0x1187fdfd0>
```



1.6 Question 4

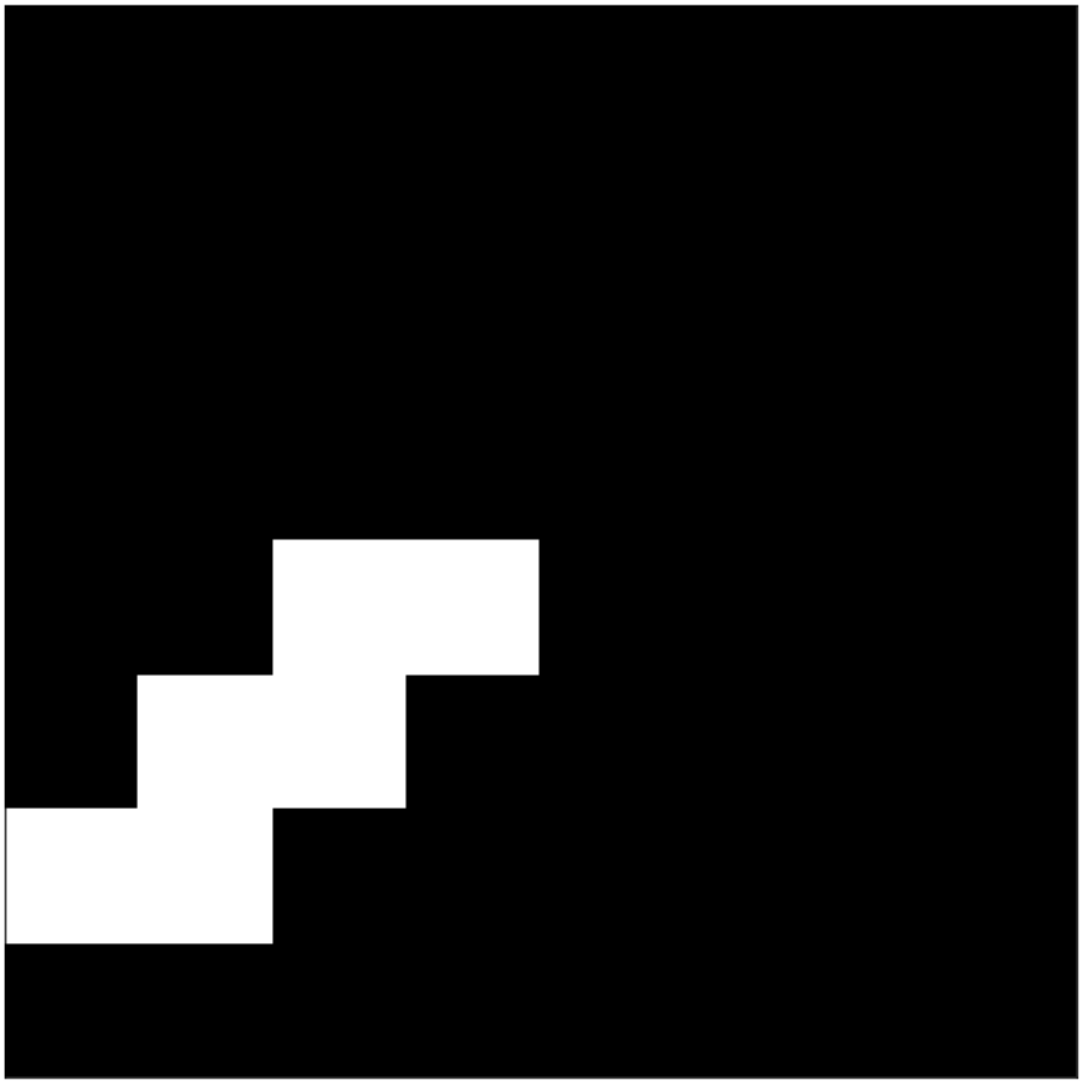
1.6.1 Principal Component Analysis (PCA)

```
In [300]: # set input points
          pts = np.array(((2.5,2.9),(0.5,1.2),(2.2,3.4),(1.9,2.7),(3.1,3.5),(2.3,3.2),(2,2.1),
                         (1,1.6),(1.5,2.1),(1.1,1.4))).T
          pts.T

Out[300]: array([[ 2.5,  2.9],
                 [ 0.5,  1.2],
```

```
                [ 2.2,  3.4],
                [ 1.9,  2.7],
                [ 3.1,  3.5],
                [ 2.3,  3.2],
                [ 2. ,  2.1],
                [ 1. ,  1.6],
                [ 1.5,  2.1],
                [ 1.1,  1.4]])
```

In [302]:
```
# plot input points
plot = np.zeros((8,8), np.uint8)
pts_x, pts_y = pts.astype(np.uint8)
plot[pts_y, pts_x] = 255
plt.imshow(plot[::-1,:], cmap='gray', interpolation='none')
```

Out[302]:
```
<matplotlib.image.AxesImage at 0x11b98d5f8>
```



```
In [303]: # calculate covariance matrix, its eigenvalues and eigenvectors
          eigval, eigvec = np.linalg.eig(np.cov(pts))
          print('  eigenvalues: ', eigval)
          print('  eigenvectors: \n', eigvec)  # cols

  eigenvalues:  [ 0.0490834   1.28402771]
  eigenvectors:
 [[-0.73517866 -0.6778734 ]
 [ 0.6778734  -0.73517866]]
```

Note: the principal components are defined as those having the largest eigenvalues.

```
In [304]: # calculate projection into a 1d line
          proj = np.matmul(eigvec.T[1], pts)*-1  # negative relation
          proj

Out[304]: array([ 3.8267016 ,  1.22115109,  3.99092891,  3.27294183,  4.67453283,
                  3.91168051,  2.89962197,  1.85415925,  2.56068527,  1.77491086])

In [319]: # plot projected line
          plot = np.zeros((8,1), np.uint8)
          plot[proj.astype(np.uint8), 0] = 150
          plt.imshow(plot[::-1,:], cmap='gray', interpolation='none')

Out[319]: <matplotlib.image.AxesImage at 0x11c2d39b0>
```

```
In [320]: # calculate inverse projection back into 2d coordinates
          inv_proj = np.matmul(eigvec,np.vstack((np.zeros(proj.shape[0]), proj)))*-1
          inv_proj
```

```
Out[320]: array([[ 2.59401922,  0.82778584,  2.70534454,  2.2186402 ,  3.16874146,
                   2.65162416,  1.9655766 ,  1.25688523,  1.73582043,  1.20316485],
                 [ 2.81330934,  0.89776421,  2.93404575,  2.40619697,  3.43661676,
                   2.87578402,  2.13174018,  1.3631383 ,  1.88256116,  1.30487658]])
```

```
In [321]: # plot backwards transformed result
          plot = np.zeros((8,8), np.uint8)
```

```
plot[inv_proj[1].astype(np.uint8), inv_proj[0].astype(np.uint8)] = 255
plt.imshow(plot[::-1,:], cmap='gray', interpolation='none')
```

```
Out[321]: <matplotlib.image.AxesImage at 0x11c303278>
```