A1_tdm47_E3

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1 EECS 531 - A1

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1.0.2 Assignment 1

Exercise 3 As with the previous two assignments, this one uses the same imports.

```
In [1]: %matplotlib inline
    import cv2
    import math
    from matplotlib import pyplot as plt
    from matplotlib import patches as patches
    import numpy as np
```

At this point, I define the correlation function. This function is the similar to the convolution function, with the absense of the initial rotation.

Some changes include:

- 1. I define the padded image with a white background in order to match the text background.
- 2. Instead of element-wise matrix multiplication, then summation, I do element-wise matrix subtraction, square each element, then sum.

```
In [2]: def correlation(img, kernel):
    #kernel = np.flip(np.flip(kernel, 1), 0) #flip the kernel on both axis

width, height, channels = img.shape
    k_width, k_height = kernel.shape

k_half_width = math.floor(k_width/2)
    k_half_width_2 = math.ceil(k_width/2)
    k_half_height = math.floor(k_height/2)
    k_half_height_2 = math.ceil(k_height/2)

ret = np.zeros(img.shape)

img_pad = np.ones((width + k_width + 1 , height + k_width + 1, channels))
img_pad[k_half_width : -k_half_width 2 - 1,
```

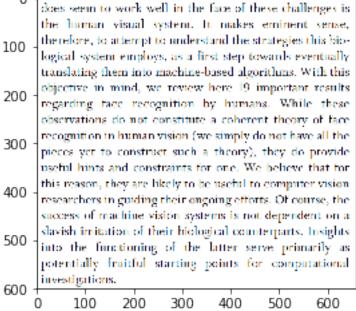
I now import the image containg the text that I will be attempting to match the letter h to. In addition, I normalize the image to range 0. - 1..

```
In [3]: img = cv2.imread('./characters.png', 1) #load all three channels, due to rendering pro
    if img is not None:
        b,g,r = cv2.split(img)
        img = cv2.merge((r,g,b))
    img = img/img.max()

In [4]: plt.imshow(img)
    plt.show()

Output

does seem to work well in the face of these challenges is
the lumnar visual system. It makes emiment sense,
therefore to relate the related the state plant to the face.
```



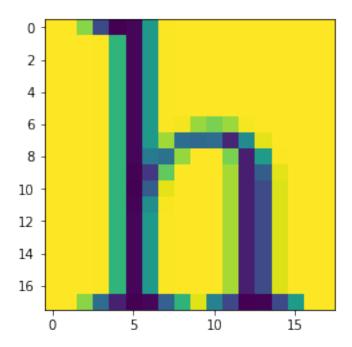
I define a function that will create a square kernel using a given template image. To make a template, I used a screenshot I took of the letter h.

This template was made with a screenshot of the text.

```
In [5]: def create_kernel(img):
    patch = cv2.imread(img, 0)
```

```
patch = patch/patch.max()
width, height = patch.shape
k_size = np.amax(patch.shape)
ret = np.ones((k_size, k_size))
x_diff = math.floor((k_size - width)/2)
y_diff = math.floor((k_size - height)/2)
ret[x_diff:k_size-x_diff,y_diff:k_size-y_diff] = patch
return ret
```

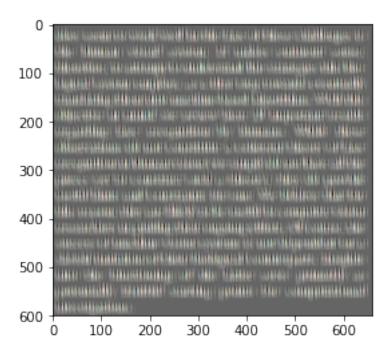
Here is how the matching template looks.



To determine where the h is located, we run the correlation function on the image. As we discussed in class, a lower correlation (not really intuitive based on how I named it) value implies that the template/kernel is more similar to the current pixel location. With this knowledge, we can determine the probability of each part of the image containing the kernel.

```
In [7]: probability = correlation(img, kernel)
```

To see a "heat map" of the likelhood of at h at each point, I have displayed the correlation below. It appears to look like a blurred image, but that's due to each letter be somewhat likely of being an h. The most likely spots have the darkest pixels.



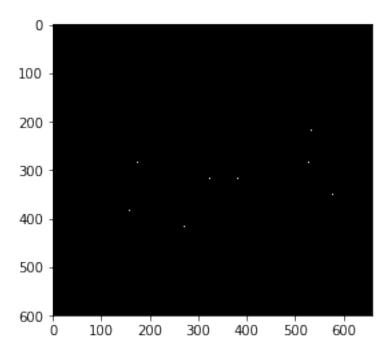
To filter the probability map, I set a limit on what classifies as an h. The purpose of this function is to select pixels used for the center of the bounding boxes.

```
In [9]: def threshold(supp, t2):
    ret = np.zeros_like(supp)

width, height, channels = supp.shape
    k_width, k_height = kernel.shape
    k_half_width = math.ceil(k_width/2)
    k_half_height = math.ceil(k_height/2)

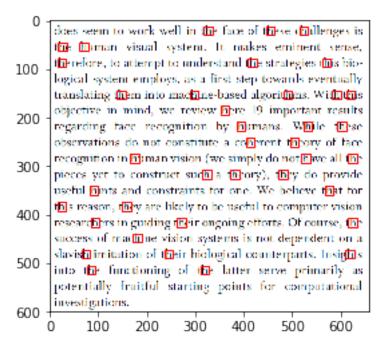
for x in range(k_half_width,width-k_half_width):
    for y in range(k_half_height,height-k_half_height):
        theta = np.sum(supp[x, y, :])
        if theta < t2:
            ret[x, y, :] = 1.
        else:
        ret[x, y, :] = 0.</pre>
```

I then output a matrix of pixels that pass the threshold and are classified as the letter h. The white dot indicates that the template matching found a high enough correlation at that location.



Here, I define a simple function that iterates through the pixels and applys a template sized bounding box at the various locations selected by the previous methods.

Here is the output of the matching process, with the selected spots highlighted by red bounding boxes. With a threshold value of 0.08, every h is correctly classified. I will explore this relationship in Exercise 4.



Number of detections: 38.0